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Environmental and health benefits of airport congestion pricing - The case of Los Angeles International Airport

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Civil Engineering

by

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2019

DEDICATION

To

my parents and friends

in recognition of their patience

Don't Worry Be Happy

Bobby McFerrin

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ABSTRACT OF THE DISSERTATION

Environmental and health benefits of airport congestion pricing - The case of Los Angeles International Airport

By

Sheng-Hsiang Peng

Doctor of Philosophy in Civil Engineering

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Airports are a source of greenhouse gases (GHG) and air pollutants such as fine particulate matter with an aerodynamic diameter under 2.5 μm ($PM_{2.5}$), which adversely affect the climate and human health. This pollution is worsening with increasing aircraft congestion. Even though aviation is the second largest source of GHG emissions in the transportation sector, it was excluded from the recent COP21 Paris Agreement. Little is known about the climate change and adverse health impacts from increasing airports congestion. The purpose of this study is to start filling this gap.

In this dissertation, I estimate congestion, health, and climate benefits from airport congestion pricing for Los Angeles International Airport (LAX), the fourth busiest airport in the world by passenger numbers in 2018. I first derive the optimal congestion fee for airports like LAX that primarily serve local and regional markets. To quantify the impacts of airport congestion pricing, I analyze one year of airport operations (2014), which corresponds to 593,547 flights (both inbound and outbound). My simulation results suggest that hourly congestion pricing would on average reduce waiting time by 2.9 minutes per

flight and annual $PM_{2.5}$ emissions by 11.4 percent, thus decreasing the environmental impacts from aircraft landing and takeoff operations (LTO), which extend as far as 19 km downwind from the airport.

An analysis of the health gains from implementing a congestion fee that accounts for air pollution cost shows that it would annually reduce premature mortality from $PM_{2.5}$ exposure by 4.6 cases, avoided hospital admissions for cardiovascular diseases by 167 cases, and avoid 8,539 lost work days. The corresponding monetary value of these health gains are $45.8 million, $21.9 million, and $1.4 million respectively (all in 2014 dollars).

For my climate change analysis, I consider both the country-level social cost of carbon (CSCC; $36 per tonne) and the global social cost of carbon (GSCC; $417 per tonne). While pricing GHG emissions with the CSCC only has a minor impact, using the GSCC helps further reduce aircraft congestion and its associated health impacts. Indeed, an aircraft congestion fee with GHG based on the GSCC would reduce premature mortality by 6 cases each year, avoided hospital admissions by 221 cases, and avoid 11,528 lost work days (95 % CI: 4,995, 18,060). The corresponding monetary value of these health gains are $60.7 million, $27.7 million, and $1.9 million respectively.

The methodology presented in this study is widely applicable. It provides engineers, planners, and policymakers a tool for reducing airport congestion and for quantifying the resulting health and climate benefits.

Chapter 1 Introduction

Over the last four decades, the number of passenger-kilometers in worldwide aviation has increased at an average rate of 5% per year (Bows-Larkin et al., 2010). As a result, many major airports around the world are operating at or beyond capacity (Jaap *et al.*, 2015), and airport congestion is becoming a major problem in many countries. High traffic volume and limited airport capacity are causing increasing air travel delays (Zhang and Czerny, 2012). In the United States, air travel delays have hit new highs since the 2000s and delays continue to plague European airlines.

A conventional solution to reduce congestion is to invest in new airport infrastructures such as new runways and terminals, but this approach is expensive and will take a considerable amount of time to design and build (Brueckner, 2009). A short-term complementary solution is to put in place technological improvements and improve air traffic control. Another alternative, in particular for airports where no significant capacity increase is foreseeable is demand management, which entails congestion pricing or restrictions on airport slots (rights to land and take off) (Brueckner, 2009).

Another increasing concern associated with airport congestion is the emission of air pollutants and greenhouse gases from airport operations. Aviation is the largest source of GHG emissions in the transportation sector after passenger vehicles and trucks (Greene et al, 2010). Aviation accounts for 11 percent of global transportation energy use and 12 percent of global transportation's CO_2 emissions (IEA, 2009, ch.7). In the U.S., aircraft emissions account for approximately 8% of U.S. transportation-related emissions or 2% of all U.S. anthropogenic emissions (U.S. Environmental Protection Agency, 2013a). Landing and takeoff operations (LTO) are the main sources of air pollution in airports. Aircraft emit approximately 80% of total emissions and ground service equipment (GSEs) accounts for the remaining 20% (Unal et al., 2005).

Besides technology improvements and the adoption of renewable jet fuel, efficiency increase in operations is expected to make an important contribution to addressing congestion and the environmental footprint of airports (IATA, 2014).

To achieve carbon neutral growth after 2020, the International Civil Aviation Organization (ICAO, 2016a) recently agreed to develop a Global Market-based Measure (GMBM). GMBM are increasingly recognized as an effective way to reduce aviation emissions, with emissions trading systems (ETSs) in place for domestic aviation and flights within the EU (ICSA, 2018). Aviation stakeholders should offset any annual increase in their GHG emissions beyond 2020 using the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) (ICAO, 2016b). One possibility is to introduce an airport congestion fee.

Emissions from aircraft engines include particulate matter (PM), carbon dioxide (CO_2), nitrogen oxides (NOx), hydrocarbons (HC), carbon monoxide (CO), sulfur oxides (SOx), and soot. Some particles, such as dust, dirt, soot, or smoke, are large or dark enough to be seen with the naked eye. In contrast, PM particulates are so small they can only be detected using an electron microscope. Despite their importance, these emissions were not regulated under the 2015 Paris climate agreement (Ciers al., 2019). The four main factors (Janic, 1999) that influence aviation emissions are:

(1) The intensity and volume of aircraft movements;

(2) The type, spatial concentration, and distribution of pollutants;

(3) Fuel consumption and energy efficiency; and

(4) The rate of renewing the aircraft fleet by introducing "cleaner" aircraft.

CO_2 and NO_X emissions from global aviation activity are expected to grow by 2.0 to 2.6% annually between 2020 and 2050 under a range of different scenarios (Owen et al., 2010). Demand for commercial aviation available seat miles is expected to grow at an annual rate of 2.9% over the next 20 years (FAA, 2018). This growth in aviation will inevitably lead to an increase in aircraft emissions unless emissions mitigation options are implemented.

Among the different air pollutants from aircraft operations, PM is most of concern. Indeed, epidemiological studies have shown that an increase in the risk of premature death is associated with exposure to $PM_{2.5}$ (Pope III et al., 2002; Laden et al., 2006; Pope III et al., 2006; Fann et al., 2012; Ghude et al., 2016). Airports operation are highly associated with elevated levels of emission downwind in the neighboring community and have further impact than roadway-traffic (Westerdahl et al., 2008).

To reduce the pollution from airport operations, three main measures can be implemented: older airplanes can be replaced with more fuel-efficient airplanes, polluting GSE can be replaced with more environmentally friendly electric alternatives, and congestion pricing can be put in place to deal with airport congestion. The first two are long-term, capital intensive policies but the third policy could be implemented over the course of a few months. However, little is known about the health benefits of these policies and airport congestion pricing to local residents. The purpose of this dissertation is to start filling this gap, and more specifically, I will quantify the health benefits of airport congestion pricing with an application to Los Angeles International Airport (LAX), which is the fourth busiest airport in the world, second in the United States.

Only a few existing models of airport congestion pricing consider environmental and health impacts. Yim, Stettler and Barrett (2013) studied the potential adverse human health impacts of emissions from UK airports. They found that the health impacts of UK airports may increase by170 % by year 2030 due to an increasing and aging population, increasing emissions, and a changing atmosphere. Schlenker and Walker (2016) linked daily air pollution exposure to measures of contemporaneous health by using an additive linear regression model for communities surrounding the twelve largest airports in California.

In order to assess airport congestion pricing policy that may be useful to mitigate the environmental and health impacts of aircraft emissions at airports, policymakers need quantitative analyses of the air quality and health improvement from policy interventions. Road congestion pricing has been widely studied in economic literature and has been proved effective (Vickrey and Sharp, 1968; Layard, 1977; Verhoef *et al.*, 1990; Lindsey and Verhoef, 2000; Eliasson *et al.*, 2009; Börjesson and Kristoffersson, 2015). Airport congestion pricing has been well studied in the last two decades (Oum and Zhang, 1990; Daniel, 1995; Brueckner, 2002; Pels and Verhoef, 2004; Zhang and Zhang, 2010; Kidokoro, Lin and Zhang, 2017). However, to the best of my knowledge, no published study has quantified the environmental and health benefits of airport congestion pricing.

In this dissertation, after reviewing selected papers, I derive the optimum airport congestion fee in Chapter 3. In Chapter 4, I present my methodology and the data I used to simulate aircraft traffic at LAX for year 2014 by using discrete-event simulation (DES), explain how I estimated air pollutant emissions using FAA's Aviation Environmental Design Tool (AEDT), and outline the procedure I relied on to disperse these emissions using EPA's AERMOD. In Chapter 5, I then explain how I assessed the health benefits of an airport congestion fee, before discussing my results in Chapter 6. Finally, Chapter 7 summarizes my conclusions and briefly discusses some limitations of my work.

Although I focus on LAX, my results should have implications for all large commercial airports. Results of this dissertation will help enhance our understanding of how airport demand managements can help curb worldwide trend of increasing airports congestion and thus help reduce aviation emission and adversely health impact.

Current regulatory practice of surface air quality generally only considers landing and takeoff cycle (LTO) emissions below an altitude of 3,000 ft and it neglects the effects of aircraft cruising emissions (Ratliff et al., 2009). However, recent regional monitoring studies indicate that surface emission can spread much further than standard LTO distance traveled (Shirmohammadi et al., 2017). Hudda et al. (2014) show that the impact zone of LAX extends 16 km downwind of the airport. In that area, airport emissions contribute at least a 2-fold increase in PM concentrations over background levels.

Results of this study will enhance our understanding of how airport demand managements can help curb worldwide trend of increasing airports congestion and thus help reduce aviation emission and adversely health impact.

List of abbreviations

Acronym	Meaning	Acronym	Meaning
AEDT	Aviation environmental design tool	JE	Jet engine
AERMOD	Air quality dispersion modeling	MOVES	Motor Vehicle Emission Simulator
APU	Auxiliary power unit	NWS	National Weather Service
ASPM	Aviation System Performance Metrics	NED	National Elevation Dataset
BenMAP	Environmental Benefits Mapping and Analysis Program	$PM_{2.5}$	Particulate matter (aerodynamic diameter less than 2.5 mm)
BPR	Bureau of Public Roads	NO_X	Nitrogen oxides ($NO + NO_2$)
C-R	Concentration-response functions	NAAQ	National Ambient Air Quality
CO	Carbon monoxide	PBL	planetary boundary layer
CO_2	Carbon dioxide	PM	Particulate matter
DES	Discrete-event simulation	RSA	Runway Safety Area
DOT	Department of Transportation	SEDAC	Socioeconomic Data and Applications Center
EPA	Environmental Protection Agency	SOx	sulfur oxides
EF	Emission factor	TFMSC	Traffic Flow Management System Counts
FAA	Federal Aviation Administration	TDOC	Total direct operating costs
FOA	First Order Approximation	USGS	U.S. Geological Survey
GSEs	Ground service equipments	VSL	Value of a statistical life
ICAO	International Civil Aviation Organization	WTP	Willingness to pay

HC	Hydrocarbons	LTO	Landing and takeoff

Chapter 2 Literature review

The literature on airport congestion pricing and on environmental and health impact of aviation is very extensive. However, limited effort has been made to integrate these two areas into a unified framework. I identify and review researches that are particularly relevant to my work. This section starts with an overview of airport congestion and congestion pricing which was first studies in road traffic. Then I discuss selected airport emissions papers and finalize this chapter with papers related to health impact of aviation pollutions.

2.1 Airport congestion pricing

In this section, I cover congestion pricing for both roads and airports, with an emphasis on the latter. Congestion pricing was first studied in urban transportation and has been extended to airport congestion studies. Some recent studies focus on the financial balance between congestion pricing and terminal and runway expansion, another solution for relaxing airport congestion and delays. I do not cover these papers since my study is related to demand management.

As a potential solution for airport congestion, congestion pricing has been widely discussed in the literature. I examine various factors that influence the design of congestion pricing. One of these factors is market structure, since airlines with market power may internalize the congestion costs they impose on their own flights (Daniel, 1995; Brueckner, 2002; Rupp, 2009; Flores-Fillol, 2010; Bracaglia et al., 2014).

Many airports are predicted to reach capacity and require expansion (Koudis et al., 2017). As a result, airport congestion emerges as a major problem in many countries. High traffic volume and limited airport capacity cause increasing air travel delays (Zhang and Czerny, 2012). Demand management aims to limit the imbalances between demand and capacity; it is a cost-effective measure to tackle increasing congestion problem in airports. Major interventions are available to provide a holistic approach to the management of airport demand and capacity.

Airport congestion and bad weather conditions are the main causes behind the prolonged taxi time of commercial aircraft (FAA, 2019a). Given the increasing willingness of airport managers to tackle airport congestion, many studies have estimated how to implement congestion scheme at airports (Levine, 1969; Brueckner, 2005; Verhoef, 2010; Czerny, 2010; Lin and Zhang, 2017; Jacquillat and Odoni, 2018) . Congestion-management approaches can be divided into two categories: price-based and quantity-based (Brueckner, 2009). Congestion Pricing is a price-based approach.

In a road system, peak hour road usage is excessive because individual users do not take into account the delays they impose on all other users. Charging a congestion fee equal to the cost of the external delays each user generates would appropriately restrict peak hour road usage (Brueckner, 2009).

Airport congestion pricing follows the same logic, but with one important difference. Individual road users are atomistic; each driver is a small part of the total traffic on the road. By contrast, in some airports and especially in congested hub airports, airlines have some market power as each airline accounts for an appreciable share of the total airport traffic (Brueckner, 2009). Several theoretical studies have pointed out that because an airline bears the cost of delay that it imposes on its other flights, it should be charged only for the delay it imposes on other carriers' flights (Brueckner, 2002; Pels and Verhoef, 2004; Brueckner, 2005; Zhang and Zhang, 2006; Brucekner, 2009).

In a hub-and-spoke network system, passengers generally travel longer distances and take more time compared to nonstop service. In return, airlines offer more frequent flights because of fewer operating routes and costs. The hub-and-spoke system is beneficial for both the airlines and the passengers (Sasaki, Suzuki and Drezner, 1999). Consequently, many airlines have established their own hub airports. However, traffic concentration significantly increases congestion at hub airports where many flights are banked in a given runway capacity (Baumgartenetal, 2014). Some airports attempt to reduce congestion by imposing peak load pricing based on conventional economic wisdom (Lin and Zhang, 2017).

The research on congestion pricing has increased markedly in recent years and congestion pricing is considered an effective measure to ease urban traffic congestion (Cheng et al., 2017). The first-best congestion pricing for road traffic scheme was studied by Walters (1961) and Morrison (1986). Just as with road pricing, an airport congestion fee is based on the marginal congestion damage (MCD) from an extra flight, which equals the increase in operating costs for all the affected airlines plus the value of the lost time for their passengers and the environmental cost of burning more fuel. However, because each airline internalizes some of its congestion, the fee does not equal the full MCD, as it would in the road case. Instead, it equals the MCD multiplied by one minus the carrier's flight share, which represents the portion of the extra congestion not internalized by the airline. This approach thus charges the carrier only for the congestion it imposes on other airlines. Moreover, such a fee would vary over the day and disappear when the airport is not crowded.

To make this point, Brueckner (2005) investigated the internalization of congestion costs in airline networks and whether the flight-share rule for congestion pricing continues to apply. His model distinguishes between peak and off-peak at a given airport. His results show that congestion fees levied on various airlines at an airport should generally be different as they should be inversely related to a carrier's airport flight share.

The current weight-based landing (and departure) fee structure in the U.S. has led to increased airport congestion. If an airline internalizes its congestion costs and considers the congestion each flight imposes on all the other flights it operates, the airport congestion fee is based on the marginal congestion damage (MCD) from an extra flight multiplied by one minus the carrier’s flight share, which equals the portion of the extra congestion that is not internalized by the airline.

If internalization does not occur, then all carriers should be charged the same congestion toll regardless of their size (Brueckner, 2009). However, Guo, Jiang and Wan (2018) proposed an alternative empirical strategy to test whether airlines internalize airport congestion corresponding to their share of traffic at the airport. They found that the hypothesis is supported by the data from Airline Origin and Destination Survey (DB1B), which suggests that airlines behavior is reasonably well-modeled with the internalization theory.

Moreover, Hu et al. (2018) estimated a congestion model that includes the costs of airlines, passengers, and the environment and show that airport congestion pricing can motivate airlines to move flights away from peak period. This study includes all 5 pollutants which is commonly found from exhausted gas from both aircraft engine, GPUs and APUs. In addition, I include social cost of greenhouse gas emission in order to tackle the increasing concern for the climate change from aviation activity.

2.2 Airport emissions studies

Studies abound about the emissions from airport and from aircraft' landing and takeoff (LTO). Over the last decade, a number of papers have analyzed the concentration of air pollutants from airports. Unal et al. (2005) first studied the impact of $PM_{2.5}$ and ozone from aircraft LTO operations on regional air quality from Hartsfield–Jackson Atlanta International Airport. They found the impacts on ozone and $PM_{2.5}$ of ground support equipment at the airport are smaller compared to the aircraft impacts. Hsu et al. (2012) quantified the contribution of LTO operations to the concentration of ultrafine particulate matter (UFP). Their results suggest positive associations between UFP concentrations and LTO activities, especially for departures. Lobo et al. (2012) present a methodology for real-time measurements of aircraft engine specific particulate matter (PM) emissions during normal LTO operations downwind of an active taxi-/runway at the Oakland International Airport.

Ashok et al. (2017) estimate the air quality and climate benefits of two measures applied to aircraft operations. They show reduced emissions from improved taxi operations by 35–38% and de-rated takeoffs (i.e., at 75% thrust) reduce PM2.5 costs by 18%. Previous studies quantify the air quality and health impacts of aviation emissions in different scales (Yim et al., 2013; Barrett et al., 2015). Although aviation is not a major source of emissions at a global level, airports may significantly affect local air quality (Schürmann et al., 2007; Westerdahl et al., 2008; Hu et al., 2009; Hudda et al., 2014; Shirmohammadi et al., 2017). Near airport aircraft operations have adverse human health and climate impacts (Stettler et al., 2011).

Yim et al. (2013) analyzed the air quality and health impacts from LTO operations, ground support equipment (GSE), and aircraft auxiliary power units (APU) in the UK. They estimated that up to 65% of the health impacts of UK airports could be mitigated by desulphurising jet fuel, electrifying GSE, avoiding the use of APU and using of single engine while taxiing. Hudda et al. (2014) measured the spatial pattern of particle number (PN) concentrations downwind from LAX with an instrumented vehicle, their results suggest that airport emissions are a major source of PM in Los Angeles that are of the same magnitude as the entire LA urban freeway network. Yılmaz (2017) estimated the pollutant gaseous emissions level of NOx, HC, CO from aircraft during different stage of the LTO cycle.

2.3 Epidemiological studies of airport operations air pollutants

Air pollutants emitted by airports activities include $PM_{2.5}$, Carbon Monoxide (CO), Sulfur Oxide (SOx), Volatile Organic Compounds (VOCs), Hydrocarbon (HC), Nitrogen Oxide (NOx), Carbon Dioxide (CO_2) and Ozone (O_3) (Lu and Morrell, 2006; Kinsey et al., 2012; ICAO, 2019). Ambient air particulate matter (PM) originates either as primary particles emitted directly into the atmosphere, or as secondary particles produced from atmospheric chemical reactions between precursor gases or between these gases and primary particles. $PM_{2.5}$ comprises particles that have aerodynamic diameters below 2.5μm (Schlesinger, 2007). Since $PM_{2.5}$ are small and light, they tend to stay longer in the air and they are able to bypass the nose and throat to penetrate deep into the lungs and even the circulatory system (Raaschou-Nielsen et al., 2013; EPA,2010).

CO is generated by incomplete combustion of carbonaceous fuels such as coal, oil, gasoline and wood and it is a colorless and odorless gas that can be poisonous to humans (Kao and Nañagas, 2009; Bauer and Pannen, 2009; Iqbal et al., 2012). Sulfur dioxide (SO_X) and particulate matters (PM) are pollutants co-existing that account for the main portion of the pollutant burden in many cities and affect the respiratory system (Rahila and Siddiqui, 2014; Yun et al., 2015). The main cancer effects are lung, blood, liver, brain and kidney cancers (WHO, 2000). The main non-cancer chronic effects of VOCs are damages to the liver, sensory effects, kidneys and central nervous system, asthma and other respiratory diseases (Rumchev et al., 2007). According to WHO (2019), adverse health consequences to air pollution can occur as a result of short- or long-term exposure. The pollutants with the strongest evidence of health effects are particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2).

Ozone is associated with respiratory dysfunction and death from respiratory diseases (Jerrett et al., 2009; Yang and Omaye, 2009). Carslaw et al. (2006) conducted a study for London Heathrow Airport and reported aircraft NO_x at least 2.6 km from the airport. Schürmann et al., (2007) showed approximately 27% of the annual mean NOx was due to airport operations at the downwind airfield boundary, declining below 15% at 2-3 km around the Zurich Airport.

Ambient $PM_{2.5}$ is a major risk factor for premature mortality and morbidity (Dockery et al., 1993; Pope III et al., 2002; Pope III et al., 2004; Brook et al., 2010). Epidemiological studies have founded robust causal associations between long-term exposure to $PM_{2.5}$ and premature mortality from respiratory diseases, heart disease, stroke, asthma and lung cancer thereby their health costs is largest among other pollutants (Pope III, 2009; Lepeuleet al., 2012). Therefore, I choose $PM_{2.5}$ to study the air quality improvement from congestion pricing.

Any assessment of the mortality risks associated with ambient $PM_{2.5}$ is contingent on assumptions about the shape of concentration-response (C-R) relationships. Typically, community particulate air pollution mortality studies assume that the effect of particulate air pollution on the logarithm of daily mortality is a linear function of the air pollution concentration (Roberts, 2004). Evidence on C-R relationships for long-term mortality from PM2.5 is predominantly based on cohort studies from North America and Europe, where concentrations are comparatively low. If estimating high concentrations, extrapolations based on linear or log-linear C-R models yield implausibly high estimates of relative risk (Pope III et al., 2011; Burnett et al., 2014). Burnett et al. (2014) developed integrated exposure-response functions (IERs) that constrain the shape of the C-R relationship using mortality data for higher exposure concentrations. This is particularly important when estimating premature mortality and morbidity in developing countries.

Our understanding of the relationship between $PM_{2.5}$ -associated chemical species and health effects has been facilitated by many contemporary epidemiological and toxicological studies. Emissions from landing and takeoffs (LTO) operations stay within the planetary boundary layer, the lowest part of the atmosphere, and it is believed that they have a more direct effect on human health than emissions at cruising altitudes. In addition, air pollution can seriously impair visibility (Hyslop, 2009).

Pollutants from local airports are considered a real public health hazard (Jung et al., 2011, Barrett et al., 2013) and they are linked to premature mortality (e.g., Yim et al., 2013). Chronic exposure to exhaust fumes could affect the operators and aircraft crew inside the airport (Schindler et al., 2013). Passengers in transit also suffer occasional exposure (Liyasova et al., 2011). Over 2 million civilian and military personnel per year are occupationally exposed to jet fuels and exhaust gases worldwide (Cavallo et al., 2006). Therefore, it is critical to study the health impacts from LTO operations at airports.

PM inhalation can increase morbidity, mortality and hospital admissions and substantially reduce life expectancy (Sapkota et al., 2012). Although in the upper atmosphere PM acts as a barrier for ultraviolet radiation, in the lower troposphere, the lowest layer of Earth's atmosphere, PM is a secondary air pollutant generated through a series of complex photochemical reactions involving reactive hydrocarbons, solar radiation and NO2 (Finlayson-Pitts and Pitts, 2000; Seinfeld and Pandis, 2006).

2.4 Aviation greenhouse gas (GHG) emissions

Kerosene-fueled provides all the energy used in commercial aviation, with jet fuel accounting for about 99 percent (McCollum, Gould, & Greene, 2009). Because air travel is projected to grow faster than highway energy use, its relative importance as a source of GHG emissions is expected to double by 2050 (Greene et al, 2010). Recorded total CO_2 aviation emissions are approximately 2% of the Global Greenhouse Emissions with the expected growth around 3-4% per year (Čokorilo, 2016). More studies on aviation GHG emission are needed to address the fast growing GHG sector.

Significant attention has been directed toward aircraft and their contribution to greenhouse gas emission (Monsalud et al., 2015). If current emission trends continue, several studies indicate that temperatures will exceed 2◦C average global warming by 2100 (Anderson and Bows, 2008; Hansen et al., 2006; Meinshausen et al., 2009; Rogelj et al., 2009; Rogelj et al., 2016).

Aviation is the second largest source of GHG emissions in the transportation sector indeed it is important to study the climate impact of aviation activities. Despite ocean and land sinks, about 55% of CO_2 emissions stay and accumulate in the atmosphere and can worsen the global climate change (Kirschke et al., 2013; Le Quéré et al., 2014). Quantification of the magnitude and uncertainty of GHG emissions in environments is critical when implementing policies to mitigate CO_2 emissions, and reducing their effects on climate change (Hutyra et al., 2014). Aviation is the second largest source of GHG emissions in the transportation sector and indeed it is important to study the climate impact from aviation activities.

Summary of selected papers for airport congestion

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Levine (1969)	To consider the possibility of imposing marginal cost pricing or congestion tolls as a mean to optimize the use of the given transportation facilities.	New York's LaGuardia Airport during the period April 1967 through March 1968. This is the most recent period for which data were available.	Examine in detail two pricing approaches to increasing the efficiency with La Guardia's runways. Full marginal cost pricing and proportional marginal cost pricing are the most efficient pricing scheme.	The use of proportional marginal cost pricing offers some of the efficiency advantages without most of the problems. It is certainly preferable to the present weight-based, value of service pricing used at most airports.
Brueckner (2005)	To investigate the internalization of congestion costs in an airline network and whether the flight-share rule for congestion pricing should apply.	Focus on the moment on a city-pair market which involves a nonstop trip between an uncongested airport and congested airport.	The model distinguishes between two travel periods at a given airport, denoted peak and off-peak.	The congestion tolls levied on the various airlines at an airport should generally be different. The tolls are inversely related to a carrier's airport flight share.
Brueckner (2009)	How price and quantity-based approaches apply to the management of airport congestion.	A single congested airport served by two airlines who interact in Cournot fashion.	A model where airlines are asymmetric and internalize congestion. Optimal congestion tolls are differentiated across carriers.	A slot-distribution regime is equivalent to an efficient regime of differentiated congestion tolls.
Zhang and Zhang (2010)	To study airport decisions on pricing and capacity investment with both aeronautical and concession operations.	Investigates the impact of carriers' self-internalization of congestion on an airport's pricing and capacity investment.	Consider two alternative airport objectives: a public airport that maximizes social welfare and a private airport that maximizes profit.	A profit-maximizing airport would over-invest in capacity while the capacity investment of the public airport will be inefficient if it is under regulatory constraints.

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Verhoef (2010)	The regulation of airline at a congested airport. Regulation should address two market failures: uninternalized congestion and overpricing due to market power.	Consider two airlines serving a single market. The airport is congested and publicly operated: airport authority chooses social surplus as its objective.	A simple model of Cournot duopolies with all demand and cost functions of interest are linear.	First-best charges should be differentiated between asymmetric airlines. Undifferentiated charges do not generally drive out the least efficient airline.
Czerny (2010)	Linear and non-linear model specifications are applied to analyze the relative welfare effects of slots and congestion pricing under uncertainty	A negative stochastic correlation between inverse airport demand and marginal external congestion costs.	First, the extended linear model specifications that introduce the airport network. Second, expected welfare under slots and congestion pricing in the extended network setting.	Congestion pricing is the right choice for single airports in a linear context, but that slots might be preferred, if non-linearities (quadratic marginal external congestion costs).
Basso and Zhang (2010)	To analyzes pricing and slot-allocation mechanisms to manage airport capacity when profits are important to an airport.	While achieving the social optimum, congestion pricing, slot trading and slot auctions do generate different amounts of revenue to an airport.	Follow the model of Brueckner (2009); There are two airlines serving a congested airport. With perfectly elastic demands, passengers of airlines 1 and 2 are willing to pay ‘‘full prices.	Congestion pricing and slot trading/slot auctioning do not lead to the same results. Total traffic is higher under slot auctions than under congestion pricing.
Simaiakis *et al.* (2014)	How to optimize aircraft pushbacks from the gate to prevent the airport surface from congestion and to reduce the time spend with engines on.	Pushback times in ASPM was used and ASDE system data was used to calibrate them between August 23 and September 24, 2010.	The pushback rate was calculated manually, using a paper spreadsheet and visual inspection of the appropriate takeoff curves.	During August 23 and September 24, nearly 17 h of gate holds were experienced and fuel burn savings from gate-holds with engines off were estimated to be between 12,250–14,500 kg.

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Czerny and Zhang (2014)	Extends the literature on airport congestion pricing by allowing carriers to price-discriminate between business and leisure passengers.	The paper derives the socially optimal airport charge when airline price discrimination is allowed, and all markets are covered.	Consider an origin–destination air travel market. There is a social maximizer who can directly choose uniform fares or discriminating business and leisure fares.	The second-best discriminating business fare exceeds the first-best uniform fare, while the second-best discriminating leisure fare is lower than the first-best uniform fare.
Silva, Verhoef and van den Berg (2014)	To analyzes efficient pricing at a congested airport dominated by a single airline.	To combine airlines' strategic interactions and airport congestion pricing in a model of dynamic congestion.	A dynamic bottleneck model of congestion and a vertical structure model that explicitly considers the role of airlines and passengers.	A Stackelberg leader interacting with a competitive fringe partially internalizes congestion.
Wan, Jiang and Zhang (2015)	None of the airport-pricing studies have differentiated the congestion incurred in the terminals from the runways.	Treated terminal congestion and runway congestion separately and studied the optimal airport charges and terminal capacity investment.	By adopting a deterministic bottleneck model for the terminal to describe traffic of passenger, and a simpler static congestion model for the runway.	If the volume of business passengers increases in airport charge, the airport will raise rather than reduce the airport charge.
Lin and Zhang (2017)	How congestion pricing and capacity investment work on a simple hub-spoke airline network by highlighting airline scheduling.	Including both schedule delay and congestion delay costs in a hub-spoke network setting.	A maximize profit problem of hub carrier given the quantities and frequencies of the other carrier.	A public hub airport requires both per-flight charges and discriminatory per-local and per-connecting passenger charges to reach the first-best outcome.

Summary of selected papers for airport pollutions and health impact papers

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Schäfer *et al.* (2003)	How do emissions from Auxiliary Power Unit (APU) of the aircraft contribute to the emission at airports.	The emission index for CO for 36 different aircraft engine types and NOx was determined and compared with the International Civil Aviation Organization (ICAO) database.	Campaigns were performed on idling aircraft at major European airports using Fourier transform infrared spectrometry and differential optical absorption spectroscopy.	For idling aircraft, CO emissions are underestimated using the ICAO database while NOx is overestimated.
Unal *et al.* (2005)	What is the impact of $PM_{2.5}$ and ozone from aircraft emissions on regional air quality from Hartsfield–Jackson Atlanta International Airport.	Aircraft landing and takeoff operations (LTO) data for Hartsfield–Jackson airport in the year 2000; the total was 423,423 LTOs.	Modeling System (EDMS) is used for estimating GSE emission. FAA has developed a first-order approximation (FOA) method where $PM_{2.5}$ emission rates are a function of Smoke Number (SN) and fuel flow rate (FFR).	Ozone and $PM_{2.5}$ impacts depend highly on meteorology. Emissions from ground support equipment (GSE) impact ozone and $PM_{2.5}$, but to a lesser extent and more locally compared to aircraft emissions.
Hsu *et al.* (2012)	To quantify contributions from landing and takeoff operations (LTO) to ultrafine particulate matter (UFP).	UFP concentrations were monitored with 1-min resolution at T.F. Green Airport in Warwick, RI, in three one-week across different seasons in 2007 and 2008.	Regression models with lag terms for flight activity (ranging from 5 min before to 5 min after the departure or arrival).	Positive associations between UFP concentrations and LTO activities, especially for departures.

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Kurniawan *et al.* (2011)	Will using different methodology to assess pollutant cause a variation in results?	Aircraft pollutant emissions factors included in the ALAQS-AV database originate from EDMS4 are similar to the ICAO Methodology.	Identification, review and comparison of various methods assessing aircraft pollutant emissions and evaluation of the reliable methods to use in terms of accuracy, application, and capability.	To provide identification, comparison and reviews of some of the methodologies of aircraft pollutant assessment from the past, present and future.
Yim *et al.* (2013)	The air quality and health impacts from LTO operations, ground support equipment (GSE), and aircraft auxiliary power units (APU) in UK airport operations.	The Weather Research and Forecasting Model (WRF) is applied to derive meteorological fields for air quality simulations. Regional chemistry-transport model CMAQ to simulate pollutant concentrations at the regional scale.	A multi-scale air quality modeling approach to assess the air quality impacts and concentration-response function to estimate early deaths occur each year.	UK airports emissions cause 110 early deaths per year. Using single-engine taxiing and fixed ground electrical power could reduce health impacts by 48% in 2030.
Yim *et al.* (2015)	How to assess the air quality and human health impacts of aviation, from airport LTO emissions to intercontinental pollution attributable to aircraft cruise.	Aviation emissions for 2006 are from FAA's AEDT. Local air quality in the vicinity of a total of 968 airports is explicitly modeled. A Monte–Carlo approach to quantify the uncertainties in calculations.	Apply a multi-scale approach to resolve the variation of $PM_{2.5}$ and ozone at different spatial scales. Global and regional air quality impacts are estimated using chemistry-transport models GEOS-Chem and CMAQ.	Global aviation emissions cause approximate16,000 (90% CI: 8300–24,000) premature deaths per year. Premature deaths due to long-term exposure to aviation attributable $PM_{2.5}$ and O3 lead to costs of $21 billion per year.

Authors (year)	Main Question	Data / Concept	Method	Main Conclusions
Masri *et al.* (2017)	How to measure PM levels for locations where there is no monitoring infrastructure.	1,845 paired daily airport visibility and aerosol optical depth (AOD) measurements collected in Iraq during a period of 2 years.	A mixed - effects multiple linear regression model was used to predict PM levels.	This novel methodology can predict $PM_{2.5}$ that were highly associated with observed averages (R2 = 0.94).
Yılmaz (2017)	What is the pollutant gaseous emissions level of NO_x, HC, CO from aircraft during the LTO cycle.	The estimation of aircraft emissions during LTO by using flight data recorded in 2010 from the State Airports Authority for Kayseri Airport, Turkey.	The International Civil Aviation Organization (ICAO) Engine emission data bank and flight data from Kayseri Airport are used for the emission calculations.	The taxi mode has the most significant portion of total LTO emissions at 48%, climb-out mode causes 29%, takeoff and approach modes are responsible for 14% and 9%, respectively.
Psanis *et al.* (2017)	What is the impacts of aviation on air quality in remote insular regions.	The sampling was conducted from 22 July to 11 August 2014 at the airport of Mytilene.	A Scanning Mobility Particle Sizer (SMPS; TSI Model 3034) was used to measure airborne particles having diameters between 10 and 500 nm, with a 3-min time resolution.	Airports serving remote insular regions should be considered as important air pollution hotspots.
Wolfe *et al.* (2019)	Develop a national-level benefit per ton estimates for emitted $PM_{2.5}$, SO_2 and NO_X for 16 mobile source including vehicles, nonroad engines and equipment, trains, marine vessels, and aircraft.	This study uses detailed source-apportionment air quality modeling to project the health-related benefits of reducing $PM_{2.5}$ from mobile sources across the contiguous U.S. in 2025.	Use the source apportionment module in the CAMx photo-chemical air quality model to tag 17 unique mobile-source sectors.	Benefit per ton of directly emitted $PM_{2.5}$ in 2025 ranges from $110,000 for nonroad agriculture sources to $700,000 for on road light duty gas cars and motorcycles.

Chapter 3. Optimum airport congestion fee: model and data

3.1 Introduction

Airport congestion and air travel delays have emerged as a major problem in many countries due to the high traffic volume (Zhang and Czerny, 2012; Gillen et al., 2016). Airport surface congestion is the main cause of increased taxi-out times, fuel burn, and air pollutant emissions at major airports in the United States (Simaiakis and Balakrishnan, 2010). As a potential solution, the introduction airport congestion fee has been widely studied in the literature (Brueckner, 2005; Verhoef, 2010; Czerny, 2010; Czerny and Zhang, 2014; Lin and Zhang, 2017).

Airlines with market power may internalize the congestion costs they impose to their own flights (Daniel,1995; Brueckner, 2002; Zhang and Zhang, 2006; Ater, 2012). To the best of my knowledge, previous airport congestion pricing studies have not considered the environmental and health impacts of aircraft congestion. In this chapter, I adapt the congestion fee proposed by Daniel (1995) to LAX and introduce both air pollutant and greenhouse gas costs.

3.2 Congestion pricing model

My starting point is Daniel's (1995) bottleneck model of airport congestion pricing, which still appears to be the most sophisticated analysis of airline congestion in the literature. Daniel (1995) derived the expression of the optimal airline congestion fee and developed a detailed simulation to analyze delays at hub airports characterized by sharp "banks" of arrivals and departures in a realistic setting, and he illustrated his framework using data from the Minneapolis-St. Paul (MSP) airport, the third largest hub-and-spoke airport for Delta Air Lines. He relied on simulations to calculate equilibrium traffic patterns, queuing delays, schedule delays, congestion fees (without accounting for pollution or greenhouse gas emissions), airport capacity, and efficiency gains. He showed that flight banks associated with a hub-and-spoke network create frequent and rapid fluctuation in airport traffic rates and demonstrated how congestion pricing can generate large savings by smoothing out demand. His model also predicts significant effects from intertemporal traffic adjustments by congestion fees.

In this dissertation, I adapt Daniel's (1995) model to Los Angeles International Airport (LAX), which is not a hub-and-spoke airport, and I modify it to incorporate environmental costs of various air pollutants emitted by aircraft's jet engine and auxiliary power unit (APU). Whenever possible, I use the same notation as Daniel (1995). To the best of my knowledge, this dissertation is the first to include environmental costs in aircraft congestion pricing.

In contrast to MSP, LAX is one of the most popular origins-destination (OD) airports in the world (LAWA, 2015). This means that LAX is the destination of most arriving passengers, as transfer passengers account for less than 2 percent of all passengers. As a result, the layover cost at LAX is minor. I therefore do not consider passenger transfer cost delays in my model.

I also assume that landing and takeoff operate independently and each use two runways according to the daily operation of LAX (see Section 4.3). Accordingly, I assume that aircraft takeoff and landing can each be represented by two independent M(t)/ M/ S/ K/ FCFS queuing systems. M(t) indicates that aircraft arrivals follow a Poisson process (Markovian) with time-dependent traffic (arrival) rates. Assuming Poisson-distributed arrivals is standard for stochastic queuing models because it greatly simplifies the queuing system (Daniel, 1995). A negative exponential distribution for interarrival times between aircrafts at LAX is an evidence that Poisson-distributed arrivals assumption closely approximates the actual and simulated traffic of LAX (Figure 1).

The second M indicates that the service time in facilities (e.g., time each aircraft spends at the runway) is also Markovian. To implement this model, I assumed that service time follows a truncated normal distribution. Because LAX operate more than 70 different type of aircraft in one day (TFMSC, 2014), the takeoff and landing time varies between aircraft. For a small aircraft like the Embraer Phenom 100, the takeoff time is as low as 0.39 minute (23.3 seconds). In this study, I assume the service time for a runway follow a truncated distribution from below of a value 0.2 min: values below 0.2 min are cut off so the range is from a minimum value of 0.20 min to positive infinity $\{0.2, \infty\}$with a mean of 0.9 minute and a standard deviation 0.1 minute.

S indicates the number of servers (runways, taxiways and gates), and K is the maximum length of a queue. I assume a flexible finite queuing capacity, K. Exceeding this capacity results in diverting aircraft to a nearby airport (such as Ontario or Long Beach airports), which rarely happens at LAX. For prioritizing service, I follow the general practice of air traffic control (ATC), which is based on the First-Come-First-Served (FCFS) rule. The M/M/S system for arrivals (or departures) is shown on Figure 2.

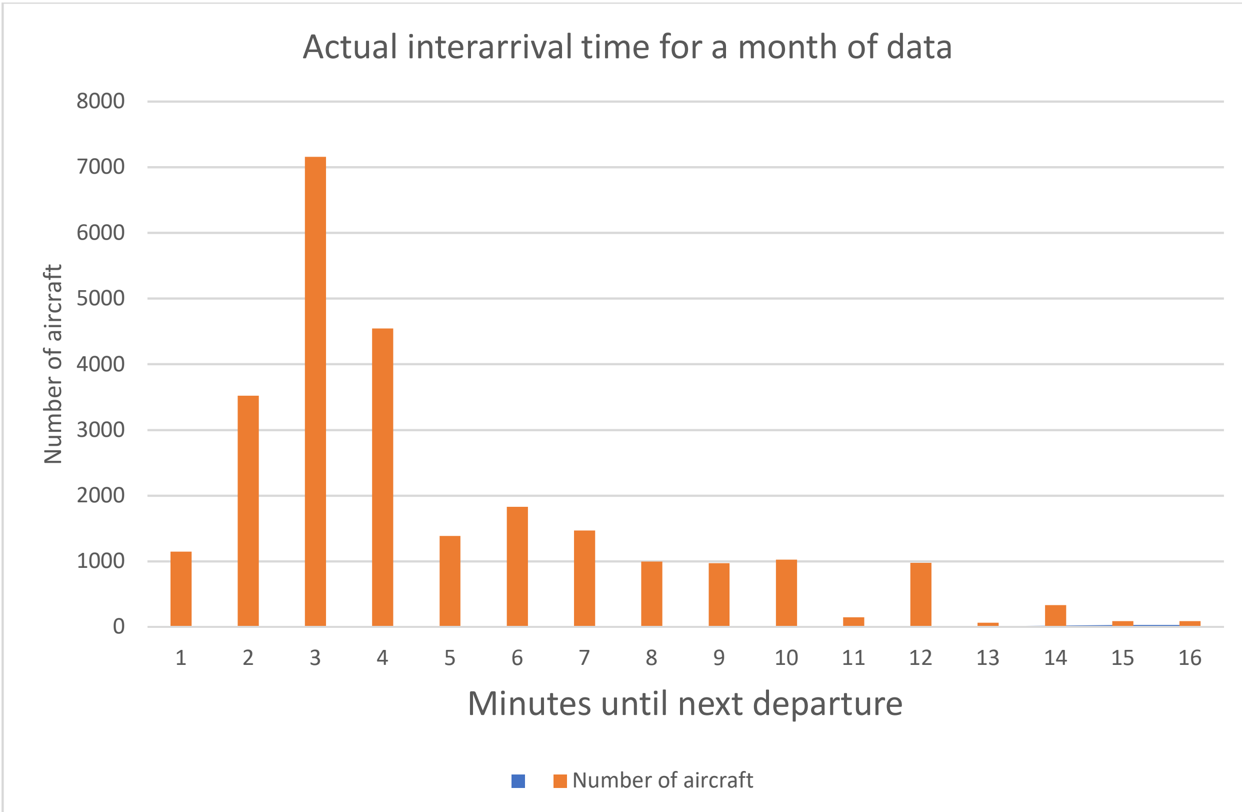


Figure 1. Inter-arrival time distributions for departure

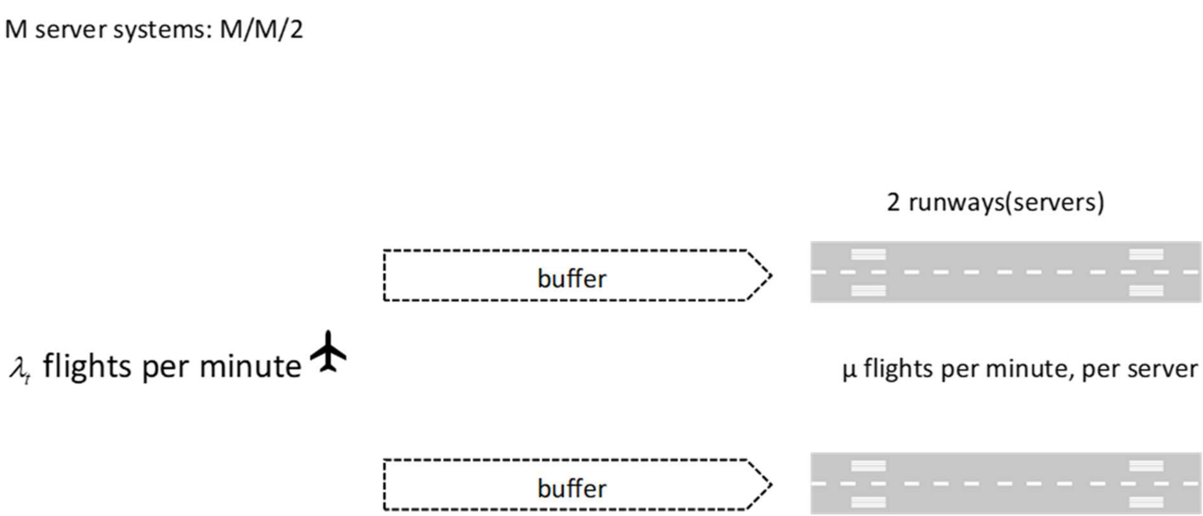


Figure 2. Arrival queue model

If all departure flights can depart the gate on time as scheduled, the departure rate of aircraft follows deterministic distribution. However, it is hard to keep everything with schedule when several kinds of group support equipment load and unload luggage, cargo and water. Every aspect of ground support operation has a variation and the combined effect could be large. The largest uncertainty is the boarding time of passengers especially for those aircraft with large passenger capacity and high loading factor.

In reality, the air traffic controller can only predict a group of aircraft that plan to depart during a specific time period. It is hard to predict which aircraft is ready and when a pilot requests to pushback and being ready to take off. Therefore, a Poisson departure rate is not unreasonable for departures at airports. Danial (1995) also showed that traffic at Minneapolis-St. Paul airport follows a Poisson distribution for both departures and arrivals.

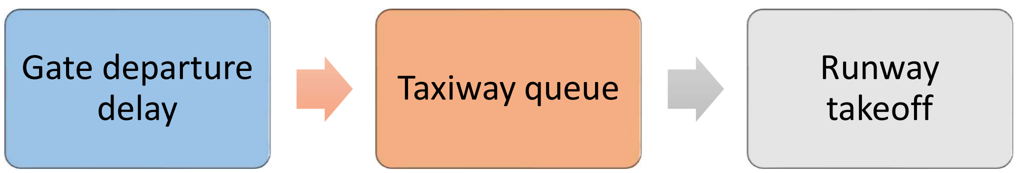
Suppose that the length of the queue is $k(\lambda_t)$ when an arriving aircraft joins the landing queue in the airway at time *t*. $k(\lambda_t)$ increases with the arrival rate λ_t, i.e. $k'(\lambda_t) > 0$, which means that if the arrival rate is larger there is a higher chance that the queue is longer when an aircraft joins the queue. To ensure that the cost function is convex and has a minimum, I also require $k''(\lambda_t) < 0$.

Let $l(k(\lambda))$ denote the waiting time required for a queue of length *k*. In that case, the next aircraft will arrive at its gate at time $t + l(k(\lambda))$ when it joins the airway queue at *t*. The scheduled arrival time is denoted by τ^A and the scheduled departure time by τ^D. Model parameters are summarized in Table 1.

For aviation, runways are the scarcest resource in the airport traffic system with one runway for most small airports and 4 runways for large airports such as LAX. Hence aircrafts waiting for a runway to land is the main source of aircraft approach queueing in airways.

Likewise, aircraft waiting for a runway to take off is the main source of aircraft departure queueing in taxiways (see Figure 3).

Panel A. Arrival process



Panel B. Departure process

Figure 3. Arrival and departure process in airports

Table 1. Model parameters

Parameter	Description
c^{TDOC}	Total direct operating costs (TDOC) per minute
c^{JE}	Environmental costs of jet emission per minute
c^{APU}	Environmental costs of the auxiliary power unit (APU)
c^{SCC}	Social cost of carbon
t	Time when an aircraft joins a queue
λ_t	Arrival rate
$k(\lambda)$	Queue length
$l(k)$	Waiting time in a queue of length k
$q_{nk}(\lambda)$	Probability that the queue is of length *k* when aircraft *n* joins the queue
τ_n^A	Scheduled arrival time for aircraft n
τ_n^D	Scheduled departure time for aircraft n
$\delta_{t+l>\tau^A}$	Dummy variable; 1 if the aircraft arrives time is later than the scheduled time τ_n^A, otherwise 0
$\delta_{t>\tau^D}$	Dummy variable: 1, if the aircraft leaves the gate after the scheduled time τ_n^D, otherwise 0
$\boldsymbol{n}_t = (1, 2, ..., N_t)$	Number of arrival aircraft scheduled at t time slots

Note: A stands for arrival; D stands for departure; JE stands for jet emission.

3.2.1 Total expected arrival cost

Following Daniel (1995), the total expected arrival cost for all arriving aircraft in the same time slot with arrival rate λ_t^A is:

$$
\begin{aligned}
C_t^A(\boldsymbol{n}_t) = {} & (c^{TDOP} + c^{JE} + c^{SCC}) \cdot \sum_{1 \le n_t \le N} \sum_{0 \le k_t \le K} q_{n_t k_t}(\lambda_t^A) \cdot l(k_t(\lambda_t^A)) \; + \\
& (c^{TDOP} + c^{JE} + c^{SCC}) \cdot \sum_{1 \le n_t \le N} \sum_{0 \le k_t \le K} q_{n_t k_t}(\lambda_t^A) \cdot [t + l(k_t(\lambda_t^A)) - \tau_{n_t}^A] \cdot \delta_{t+l>\tau^A}
\end{aligned}
\qquad (1)
$$

where $\delta_{t+l>\tau^A} = \begin{cases} 1, \text{ if } t + l(k_t(\lambda)) > \tau_{n_t}^A, \\ 0, \text{ otherwise.} \end{cases}$

The total expected arrival cost is the sum of the expected queuing cost (the first part of Equation 1) and the expected gate arrival delay cost (the second part of Equation 1). The expected queuing cost is the product of a unit cost ($c^{TDOP} + c^{JE} + c^{SCC}$), which include total direct operating costs (TDOC) per minute and jet emission environmental costs per minute, by the expected queuing time. The expected queuing time is the waiting time required in the *k* length landing “airway queue”, $l(k_t(\lambda))$, weighted by the probability that the queue is of length *k* when another aircraft joins the arrival queue, $q_{n_t k_t}(\lambda_t^A)$, summed over all possible value of the possible queue length *k* and scheduled aircraft *n*.

Likewise, the expected gate arrival delay cost is the product of a unit cost (same as for the first term) and the expected gate arrival delay. The latter is the difference between the gate arrival time $t + l(k_t(\lambda))$ and the scheduled arrival time $\tau_{n_t}^A$.

3.2.2 Total expected departure cost

Similarly, the total expected departure cost for all aircraft in the same time slot with departure rate λ_t^D can be written:

$$C_t^D(\boldsymbol{n}_t) = (c^{TDOC} + c^{APU} + \frac{1}{2}c^{JE} + c^{SCC}) \cdot \sum_{1 \le n_t \le N} (t - \tau_{n_t}^D) \cdot \delta_{t > \tau_{n_t}^D} \quad + \quad (c^{TDOC} + c^{JE} + c^{SCC}) \cdot \sum_{1 \le n_t \le N} \sum_{0 \le k_t \le K} q_{n_t k t}(k_t) \cdot l(k(\lambda_t^D)) \tag{2}$$

where $\delta_{t > \tau_{n_t}^D} = \begin{cases} 1 & , \ if \ t > \tau_{n_t}^D \\ 0 & , \ otherwise \end{cases}$

For departing aircraft, the total expected departure cost is the sum of the expected gate departure delay cost (the first part of Equation 2) and the expected queuing cost (the second part of Equation 2).

The gate departure delay is the difference between the gate departure time t and the scheduled departure time $\tau_{n_t}^D$. Unlike for arriving aircraft, the taxi queue always happens after the gate departure delay. In this case, the unit cost is the sum of four terms: total direct operating costs (TDOC) per minute, auxiliary power units (APU) costs per minute, social cost of carbon (SCC) per minute, and half the jet emission environmental costs per minute because jet engines are at half power at the gate .

The expected queuing cost for departure is defined as the waiting time in the *k* length "taxiway queue" weighted by the probability that the taxiway queue is of length *k* when an aircraft joins the departure queue, $q_{n_t k_t}(\lambda_t)$, summed over all possible value of scheduled aircraft *n* and queue length *k*.

3.2.3 The airport's optimization problem

As in Daniel (1995), I assume that the airport chooses the maximum aircraft arrival rates ($\widehat{\lambda_t}$) in each time slot, according to the capacity of its runways and facilities, in order to minimize the expected total social costs over all time slots. Therefore, the decision variables for the airport are the maximum arrival rate in each time slot, and its objective is to minimize the expected cost with respect to a series of maximal arrival rate $\hat{\lambda}_1, \widehat{\lambda_2}, ..., \widehat{\lambda_t}$ for each time slot. This can be written:

$$\min_{\hat{\lambda}_1,...,\hat{\lambda}_t} \sum_{t=1}^{21} \sum_{n=1}^{n_t} P_n^t \cdot C_t(\widehat{\lambda_t}) \tag{5}$$

The corresponding first-order necessary conditions for cost minimization in each time slot are

$$\sum_t \frac{\partial P_n^t}{\partial \widehat{\lambda_t}} \cdot C_t(\hat{\lambda}) + \sum_t \sum_n p_n^t \cdot \frac{\partial C_t(\hat{\lambda})}{\partial \widehat{\lambda_t}} = 0 \tag{6}$$

A total of 21 time slots will have 21 corresponding first-order necessary conditions for cost minimization.

3.2.4 The airlines' optimization problem

To model the behavior of airlines, I assume that each individual airline independently chooses its schedule to minimize its private costs. Given maximum departure or arrival rates $\hat{\lambda}_1, \widehat{\lambda_2}, ..., \widehat{\lambda_t}$ for each time slot (indexed by *t*), an airline chooses the best time slot (i.e. arrival rate) to schedule its aircraft in order to minimize its private expected costs. The airline's objective function can be written:

$$\min_{\lambda_t} \sum_{t=1}^{21} p_n^t \cdot C_t(\lambda)$$

$$subject\ to\ \sum_{n=1}^{n_t} \lambda_t^n \leq \widehat{\lambda_t}; \tag{7}$$

$$p_t^n \geq 0;\ \lambda_t^n \geq 0;\ \widehat{\lambda_t} \geq 0$$

A standard assumption in the airport congestion literature is that an airline manager regards total expected cost $C_t(\lambda)$ in each time slot as exogenous and ignores the effect of their scheduling decisions on expected costs $C_t(\lambda)$ (Daniel, 1995; Daniel and Harback, 2008; Aravena et al., 2019). The airline's first-order necessary conditions for cost minimization is then given by

$$\sum_t \frac{\partial p_n^t}{\partial \widehat{\lambda_t}} \cdot C_t(\hat{\lambda}) = 0 \tag{8}$$

3.2.5 Optimum congestion fee

The airport can design an optimal schedule by imposing a congestion fee equal to the externality of congestion. I follow Daniel's (1995) method of calculating the congestion fee. I first derive the first-order condition of the objective functions for both the airport and the airlines. The congestion fee at each time slot equals the difference between the social-cost-minimizing airport planner's first-order condition and the individual airline's first-order condition, which is, by definition, the external social cost if individual airlines act to maximize their own payoff. The congestion fee at time $t^{'}$ is then:

$$F_{t^{'}} = \sum_{t^{'}} \sum_{n_t} p_n^{t^{'}} \cdot \frac{\partial C_{t^{'}}(\hat{\lambda})}{\partial \widehat{\lambda_t}} \tag{9}$$

Daniel also proved that Equation 6 is the congestion fee that airports should charge in each time slot. It equals the social external cost of adding one more aircraft in a congestion time slot from an individual airline to all the other airlines. In other words, it is the external cost imposed by one additional aircraft and it should be paid by the airline that adds the additional aircraft during the time slot considered.

3.3 Optimum airport congestion fee: a special case

To operationalize the congestion fee, I assume that both aircraft arrival and departure follow a Poisson Process (Wolff, 1982; Barbour et al., 1992). Poisson processes are widely used for modeling arrivals and departure. For a Poisson process with an arrival rate λ_t, and given $t > 0$, the probability mass function (PMF) that the number of arrivals equals $k(\lambda_t)$ in $(0, t]$ is given by (Haight, 1967; Gallager, 2012):

$$q_{nk}(k) = \frac{(\lambda_t)^k e^{-\lambda_t}}{k!} \tag{10}$$

After replacing all $q_{nk}(k)$ with the expression from Equation (7) in Equation (1), I obtain the following expression for the total expected arrival cost with arrival rate λ_t^A,

$$\begin{aligned} C_t^A(\boldsymbol{n}) = {} & (c^{TDOP} + c^{JE}) \cdot \sum_{1 \le n_t \le N} \sum_{0 \le k_t \le K} \frac{(\lambda_t^A)^{k_t} e^{-\lambda_t^A}}{k!} \cdot l_{n_t}(k_t(\lambda_t^A)) \ + \\ & (c^{TDOP} + c^{JE}) \cdot \sum_{1 \le n_t \le N} \sum_{0 \le k_t \le K} \frac{(\lambda_t^A)^{k_t} e^{-\lambda_t^A}}{k_t!} \cdot [t + l_{n_t}(k_t(\lambda_t^A)) - \tau_{n_t}^A] \cdot \delta_{t+l > \tau^A} \end{aligned} \tag{11}$$

$$\text{with } \delta_{t+l > \tau_{n_t}^A} = \begin{cases} 1 \ , & \text{if } t + l(k(\lambda)) > \tau_{n_t}^A \\ 0 \ , & \text{otherwise} \end{cases}$$

The congestion fee equals the expected increase in costs for all aircraft in time interval $(0,t]$ imposed by an increase in the arrival rate.

Let us now discuss the partial derivative of the arrival cost function in Equation (8) with respect to the arrival rate λ_t. The first order derivative of total expected cots for arriving aircraft is:

$$\begin{aligned}
\frac{\partial C_t^A}{\partial \lambda_t}(\boldsymbol{n}) &= (c^{TDOP}+c^{JE})\cdot \sum_{1\le n_t\le N}\ \sum_{0\le k_t\le K} \frac{[k_t(\lambda_t)^{k_t-1}-(\lambda_t)^{k_t-1}]\cdot e^{-\lambda_t}}{k_t!}\cdot l_{n_t}(k_t(\lambda_t))+(\frac{(\lambda_t)^{k_t}e^{-\lambda_t}}{k_t!})\cdot(\frac{\partial l}{\partial k_t}\frac{\partial k_t}{\partial \lambda_t})\ + \\
&\quad (c^{TDOP}+c^{JE})\cdot \sum_{1\le n_t\le N}\ \sum_{0\le k_t\le K} [\frac{[k_t(\lambda_t)^{k_t-1}-(\lambda_t)^{k_t-1}]\cdot e^{-\lambda_t}}{k_t!}\cdot[t+l_{n_t}(k_t(\lambda_t))-\tau_{n_t}^A]+(\frac{(\lambda_t)^{k_t}e^{-\lambda_t}}{k_t!})\cdot(\frac{\partial l}{\partial k_t}\frac{\partial k_t}{\partial \lambda_t})]\cdot\delta_{t+l>\tau^A} \\
&= (c^{TDOP}+c^{JE})\cdot \sum_{1\le n_t\le N}\ \sum_{0\le k_t\le K} \frac{[k_t(\lambda_t)^{k_t-1}-(\lambda_t)^{k_t-1}]\cdot e^{-\lambda_t}}{k_t!}\{l_{n_t}(k_t(\lambda_t))+[t+l_n(k_t(\lambda_t))-\tau_{n_t}^A]\}+(1+\delta_{t>l-\tau^A})(\frac{(\lambda_t)^{k_t}e^{-\lambda_t}}{k_t!})\cdot(\frac{\partial l}{\partial k}\frac{\partial k_t}{\partial \lambda_t})
\end{aligned}$$

$$with\ \ \delta_{t+l>\tau_{n_t}^A}=\begin{cases}1 & ,\ if\ \ t+l(k_t(\lambda))>\tau_{n_t}^A\\ 0 & ,\ otherwise\end{cases}$$

(12)

Likewise, the partial derivative of the departure cost function given by Equation (2) with respect to the arrival rate is:

$$\frac{\partial C_t^A(\boldsymbol{n})}{\partial \lambda_t}=(c^{TDOP}+c^{JE})\cdot \sum_{1\le n_t\le N}\ \sum_{0\le k_t\le K} \frac{[k_t(\lambda_t)^{k_t-1}-(\lambda_t)^{k_t-1}]\cdot e^{-\lambda_t}}{k_t!}\cdot l_{n_t}(k_t(\lambda_t))+(\frac{(\lambda_t)^{k}e^{-\lambda_t}}{k_t!})\cdot(\frac{\partial l}{\partial k_t}\frac{\partial k_t}{\partial \lambda_t})$$

(13)

The congestion fee for arrivals and departures in time interval $(0,t]$ is given by replacing $\frac{\partial C_t^A(\boldsymbol{n})}{\partial \lambda_t}$ in Equation (6) with Equation (9) and (10) respectively.

The parameters needed to calculate this expression include the cost of total direct operations (c^{TDOC}), cost of engine (c^{JE}), cost of APU (c^{APU}), arrival rates (λ_t^A) and departure rates (λ_t^D) for each time slot, length of queue ($l(k)$), number of flights, arrival time between two difference aircraft, difference between two queue length, difference between two queue time and difference between two arrival rate. All the aforementioned values are discussed in Section 4.5. The hourly congestion fees for peak and off-peak seasons are calculated from Equation 6, 9 and 10 using the R software. The package of "deriv" was install and used to facilitate the calculation of differentiation functions. My R code for calculating the congestion fee is presented in Appendix D. Results are discussed in Chapter 6.

3.4 Data

In this section, I will discuss the source and the value of the parameters needed to operationalize my model. They include average total direct operating costs (TDOC), social cost of emissions from aircraft engines and APU emissions and social cost of carbon (SCC).

3.4.1 Total direct operating costs

According to Airlines for America (2017), the average total direct operating costs (TDOC) of aircraft block time (taxi plus airborne) for U.S. passenger airlines was \$68.48 per minute in 2017, which include crew costs (\$22.67 per minute), fuel costs (\$21.27 per minute), maintenance and aircraft ownership (\$12.37 and \$9.40, respectively), and all other costs (\$2.70). These costs are based on the US Department of Transportation (DOT) Form 41 data for U.S. scheduled passenger airlines. I normalized the TDOC by comparing consumer price indices (CPIs) between year 2017 and 2014 and it is \$65.23 per minute in the 2014 term.

$$TDOC_{2014} = TDOC_{2017} \cdot \frac{CPI_{2014}}{CPI_{2017}} \tag{14}$$

3.4.2 Social cost of emissions from aircraft engines and APU emissions

In this subsection, I discuss the value of environmental cost of APU and jet engine emissions (c_k), country-level cost of carbon (CSCC) and the global-level cost of carbon (GSCC). Departure aircraft use auxiliary power unit (APU) as an additional energy source to power air conditioners and lights in aircraft cabins while parked at a gate. Most importantly, operating APU negate the need to start all aircraft's main engines so their use results in substantial reductions in fuel consumption and air pollutant emissions. Therefore, the per minute environmental cost for departing aircraft is the emission cost of APU, c^{APU}, plus one half of environmental cost of jet engines, $c^{JE}/2$. Using APUs is also beneficial during the aircraft taxi stage. At large or busy airports where the taxi time to and from the runway can exceed 15 minutes, single engine taxi can bring considerable benefits (Airbus, 2004).

The environmental cost of APU and jet engine emissions have received some attention from the literature (Lu and Morrell, 2006; Kinsey et al., 2012; ICAO, 2019). Here, I followed Lu and Morrell (2006) to estimate the social cost of aircraft engines and APUs in the airport congestion fee model described above. The social costs are derived from weighting emission indices (kg/h) with fuel flow rate (kg/h) and standard LTO modes time (hour), applying the unit social cost for each pollutant. Second, the annual social cost is determined by summing across the annual aircraft movements and emissions inventory. Standard LTO modes include taxi-out, takeoff, climb, approach and taxi-in.

$$F_{ij} = t_i \cdot f_i \cdot e_{ij} \tag{3}$$

where t_i is the time spent during the ith mode ; f_i the fuel flow during the ith mode; e_{ij} the emission indices of the jth pollutant during the ith mode.

Table 2 shows the social cost of different pollutant emissions. I calculate the social cost (c_k) for aircraft using Equation 4:

$$c_k = \sum_{j}^{5} \sum_{i}^{5} \delta_i \cdot F_{ij} \cdot U_j \tag{4}$$

where δ_i is the weight for each of the 5 mode of LTO, they include taxi-out, takeoff, climb-out, approach and taxi-in modes (Appendix E for detail). U_j is the unit social cost for the 5 different pollutants listed in Table 2 (US$/kg), the jth means pollutant j.

Table 2. Environmental costs of APU and jet engines

Source	CO	NO_X	HC	SO_X	PM
Dones et al. (2005)	0.02	3.3-3.6	--	3.3-12.18	362.8-681.3
Schipper (2004)	--	2.13-43.2	0.82-4.27	1.74-46.52	5.78-121.73
Gallagher and Taylor (2003)	--	1.1-13.6	--	1.1-3.7	--
Average	0.02	11.3	2.55	11.42	292.88

Note: costs are in US$ per kg.

3.4.3 Global and country-level social cost of carbon

The social cost of carbon (SCC) is a commonly employed metric to quantify the expected economic damages or benefit from carbon dioxide (CO_2) emissions or reduction (and more generally the CO_2 equivalent of various greenhouse gases). To estimate the climate cost of greenhouse gases emitted by aircraft engines and APUs, more than one options is available because it could reflect expected damages at different scales (region, country, global). The social cost of carbon (SCC) represents the economic cost associated with climate damage (or benefit) that results from the emission of an additional ton of carbon dioxide (tCO_2). The SCC provides an economic valuation of the marginal impacts of climate change. Here, I consider the country-level cost of carbon (CSCC) and the global-level cost of carbon (GSCC).

To estimate the CSCC for LAX, I multiplied the annual aviation CO_2 emissions of LAX by the US Environmental Protection Agency's median country-level cost of carbon (CSCC) of $36 per ton in 2015 (adjusted with a 3% discount rate) (US EPA, 2016). For the median global social cost of carbon (GSCC), I used $417 per ton, as suggested by Ricke et al. (2018).

The CSCC estimates the amount of marginal benefit expected to occur in an individual country due to reduced CO_2 emission, while the GSCC is the sum of CSCC values for all countries. Following the International Civil Aviation Organization (ICAO) (2013) standard, I assume that burning 1 kg of jet fuel generates 3.16 kg of CO_2. This is also the value used to report aviation CO_2 emissions to the United Nations Framework Convention on Climate Change (UNFCCC) (ICAO, 2013).

3.4.4 Summary of model parameters

The parameters needed to calculate this expression include cost of total direct operations, cost of engine, cost of APU, arrival rates and departure rates for each time slot, length of queue, number of flights, arrival time between two difference aircraft, difference between two queue length, difference between two queue time and difference between two arrival rate. All the aforementioned values can be found in the process of conducting discrete-event simulation (DES) that I will discuss in Chapter 4.

My R code for calculating the congestion fee is presented in Appendix D. Because the flights at LAX are spread out evenly throughout weekdays and weekend. I only study the congestion fees for different seasons. The congestion fee for peak season and off-peak seasons and the airport traffic pattern before and after the implementation of congestion fee are presented and discussed in Chapter 6.

Chapter 4 Methodology and data for estimating and dispersing emissions

4.1 Introduction

In this chapter, I present my methodology and the data used to estimate and disperse the emissions of $PM_{2.5}$. After presenting my study area, I first apply discrete-event simulation (DES) to simulate the aircraft's operation of LAX. I then present the aviation environmental design tool (AEDT), which I used to estimate the emission inventory of aircraft taxi and LTO. Third, I discuss the air quality dispersion modeling (AERMOD) tool I was used for dispersing the emissions of pollutants.

4.2 Study area

Los Angeles International Airport (LAX) is the fourth busiest airport in the world, and second in the United States in terms of commercial passenger volumes. It served over 87.5 million passengers in 2018. It is the main entryway into Los Angeles and Southern California (LAWA, 2019). LAX has 4 runways (Figure 5); two are located north of its terminal (06L-24R and 06R-24L) and 2 are to the south (07L-25R and 07R-25L). Because of the strong prevailing west-to-east winds, all four runways are oriented east-west. Approximately 97% of departures and 95% of arrivals occur in a westward direction (FAA, 2014). There is no residential and businesses zone between the western boundary of the airport and the Pacific Ocean, which sees only very light vehicle traffic. Most residents in my study area live on the eastern side of the airport, so they can be exposed to emissions from aircraft due to the prevailing west-to-east wind direction.

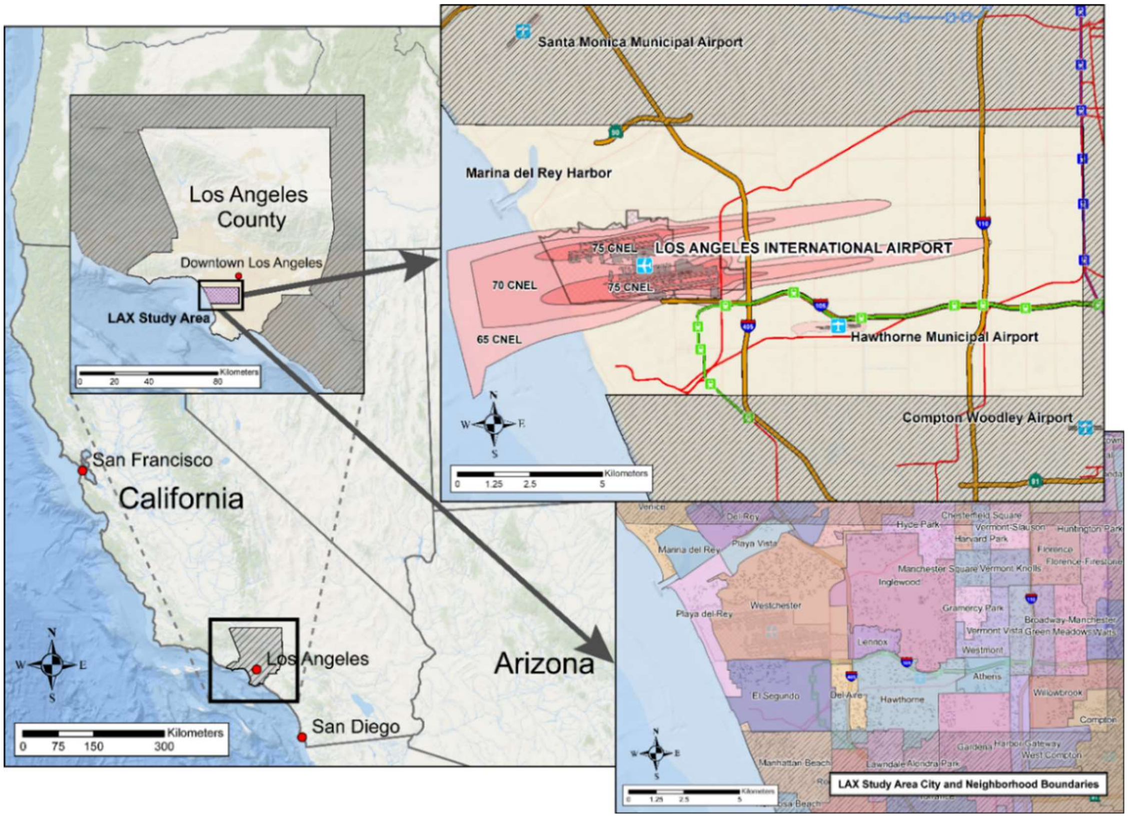


Figure 4. Study area

(Source: USGS&ESRI)

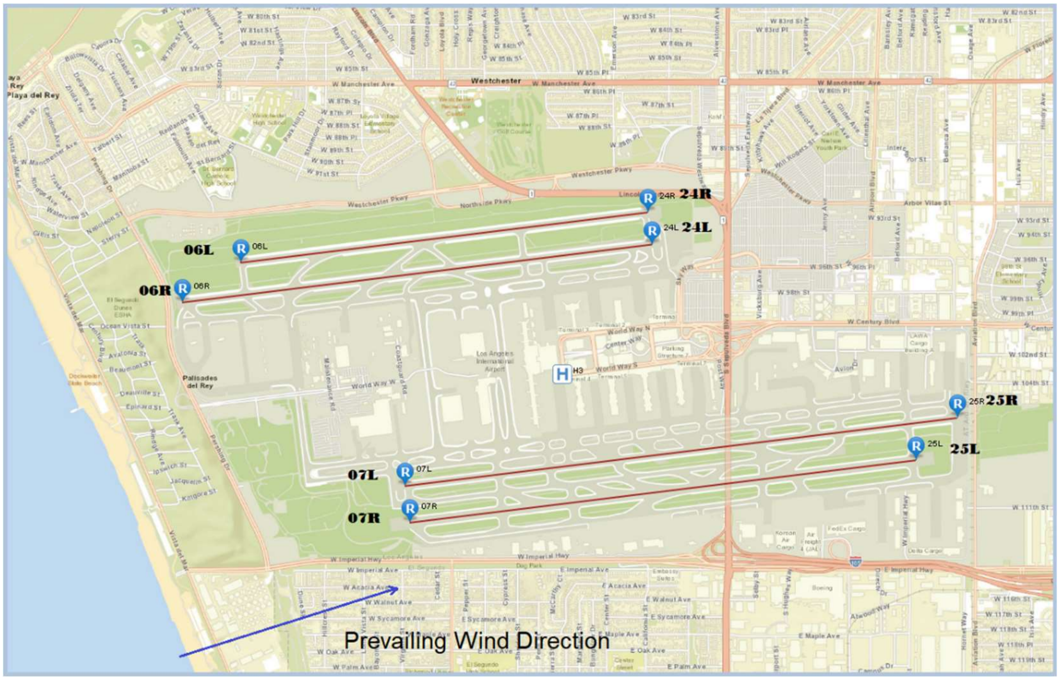


Figure 5. Airport Layout

(Source: AEDT2d)

Los Angeles international airport (LAX), which is projected to enplane 66.1 million passengers in 2045 (FAA, 2016), is also experiencing increasing congestion and rising taxi times for inbound and outbound flights, a good indicator of the level of congestion. The average taxi-in time rose from 8.4 minutes in 2009 to 12.9 minutes in 2016, a 54 % increase in only 7 years. In the same time, the average taxi-out time rose from 14 minutes in 2009 to 17.1 minutes in 2016, a 22 % increase (FAA, 2017). See Figure 6 for an evolution of taxi times at LAX. Chronic congestion forces aircraft to burn more fuel, which generates more air pollutants, and increases the cost of flying.

Figure 6. Taxi time of LAX

(FAA, 2017)

4.3 Aircraft westerly operations

When an aircraft takes off into the wind, it helps the aircraft achieve "wheels up" speed faster and requires a shorter runway. Well-designed airports capitalize on the physics of flight. This explains that, since the main winds at LAX Airport blow from the west, all four of its runways are oriented from east to west. As a result, during most of daytime, landing aircraft approach the airport from the east and departure aircraft depart the airport to the west.

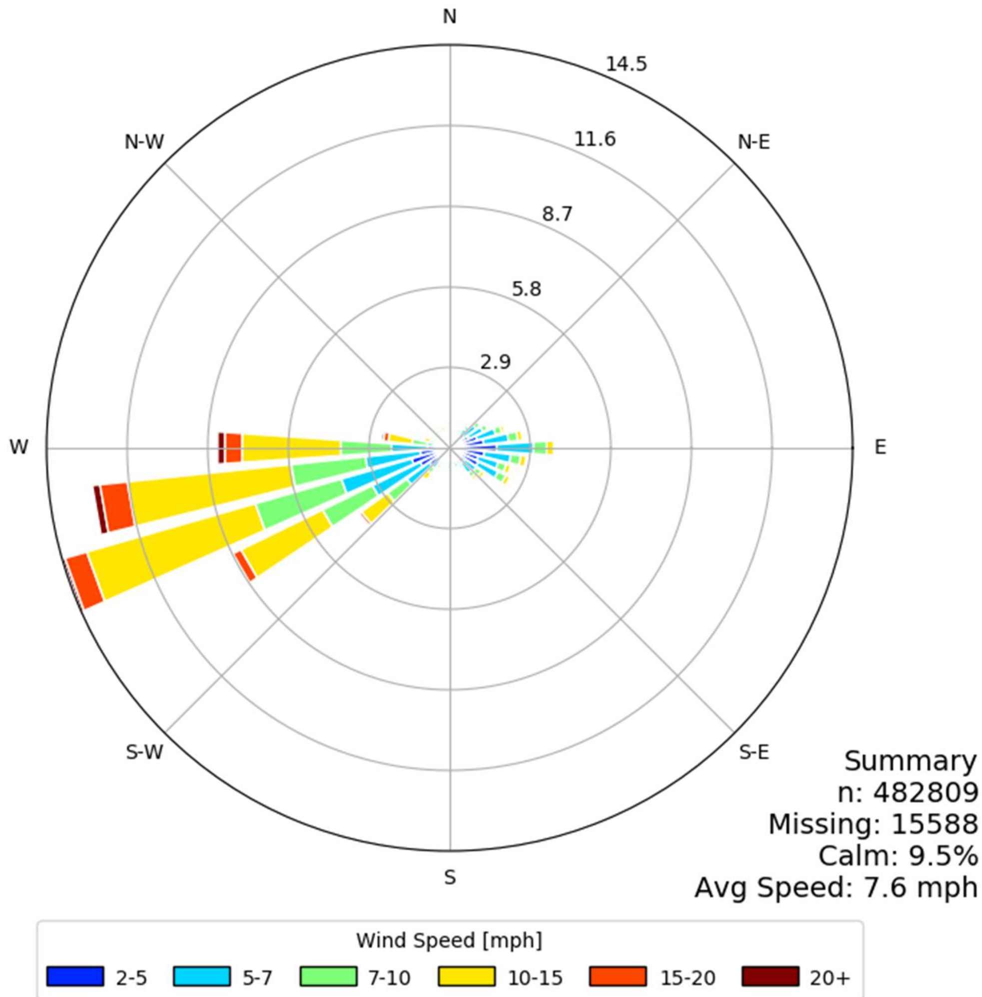


Figure 7. The year 2014 wind rose for Los Angeles International Airport

Source: Iowa State University (2019)

This mode of operations routes louder departing aircraft to the west over the ocean primarily from the two "inner" runways that are further from surrounding communities, while arriving aircraft fly from east to west over the communities on the eastside of LAX, including the cities of Los Angeles and Inglewood, and the communities of Athens and Lennox. Hence, arrivals and departures are considered to be independent. The average wind speed in 2014 was 7.6 mile per hour and 9.5% of the time wind was calm (see Figure 7).

4.4 Flight data records

In this study, I use high-resolution (1 hour) aircraft departure and arrival activity data recorded by the Federal Aviation Administration (FAA) and assembled by the Traffic Flow Management System Counts (TFMSC) at Los Angeles International Airport between January 1st, 2014, December 31st, 2014. TFMSC is designed to provide information on traffic counts by airports for various data groupings such as aircraft type or by hour of the day (FAA, 2019). The range of temperatures during the study period (4–39 ^{o}C) does not have a significant impact on operations and no significant rainfall and snowfall events occurred. Major aircraft technical issues (e.g., landing with one engine malfunction) were removed from my dataset. I also conducted thorough data checks to remove aircraft operations classified as irregular.

I chose to analyze year 2014 because Los Angeles International Airport underwent major airside improvements including runways and taxiways periodic maintenance and construction of new Runway Safety Area (RSA) zone at the ends of each runway starting in 2015 (LAWA, 2016). This required periodic runways closures. Under normal operating conditions, aircraft move from east to west for both landing and takeoff, as explained above. I chose to analyze only aircraft operations from 5 AM to 1 AM the next day because there is no congestion between 1 AM and 5 AM. Overall, I analyzed 296,482 landing and 297,065 takeoff events, which represent 99.5% of all landings and 99.7% of all takeoff activities at LAX during the study period.

4.5 Integrated assessment methodology

Figure 8 presents an overview of my methodology to estimate emissions and health impacts from aircraft and LTO operations. In this chapter, I examine the first three components in turn.

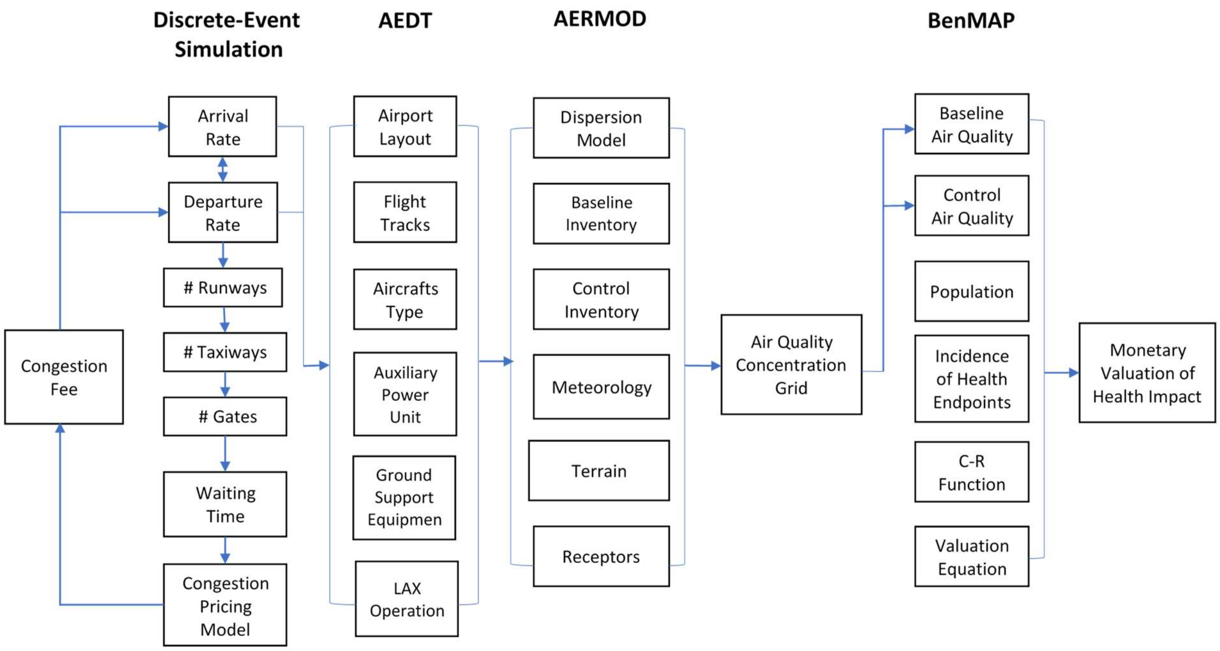


Figure 8. Methodology

4.6 Discrete-event simulation package for R (SIMMER)

To simulate aircraft operations at LAX, I applied discrete-event simulation (DES) and used flight data downloaded from TFMSC. Discrete-event simulation has been widely used to study queueing in a variety of fields. These include, for example, patient flow in hospitals (Jacobson and James 2006; Hung et al., 2007), production scheduling and supply chain (Vaidyanathan and Young, 1998; Windisch et al., 2015), and the analysis of communication networks (Egea-Lopez et al., 2005;

Ucar et al., 2018). DES is particularly effective when providing a rapid and less expensive alternative to identify unknown risks to airport traffic before any policy implementation.

SIMMER is a process-oriented and an open-source DES package of the R language (Ucar and Arturo, 2017). I started by setting up an air traffic trajectory for LAX, arrival and departure rate for each study hour, and the number of resources or facilities: 4 runways (2 in the south complex, 2 in the north complex), 17 taxiways (8 in the south complex, 9 in the north complex) and 132 gates in 9 terminals (FAA, 2018). In addition to the arrival rate and source used, service time of each facility is required, the data can be download from Traffic Flow Management System Counts (TFMSC) and Los Angeles World Airports (LAWA) website.

The average time required in each facility was obtained from Los Angeles World Airports (LAWA, 2018). After making sure resources are seized and released as expected, I simulated aircraft traffic, queues and waiting time, before and after implementing a congestion fee. In particular, I confirmed that simulated aircraft operations could replicate the aircraft traffic at LAX. After imposing the congestion fee calculated via Equation 6, I applied a new arrival rate for each study hour and simulated the new resulting aircraft traffic. Results from SIMMER for the before- and after-fee cases served as inputs for the airport emission inventory model (AEDT) in the next step of my methodology.

4.7 Aviation environmental design tool (AEDT)

An emissions inventory tallies the masses of various pollutants emitted within a given geographic region during a specific period. In this study, emission inventory estimates are based on the U.S. Federal Aviation Administration's (FAA) Aircraft Environmental Design Tool (AEDT 2d). To model hourly airport operation emission inventory for a whole year (2014), I built a spatially and temporally resolved model of LAX using the AEDT model.

Because emissions stemming from the operation of commercial aviation are highly interdependent throughout all phases of flight, I chose AEDT for this work because this software was designed to dynamically estimate aircraft performance in space and time, and to compute fuel burn, and the emissions of various air pollutants. Recent studies have used AEDT to assess commercial aviation emissions (Wilkerson et al., 2010), global mortality of aircraft cruise emissions (Barrett et al., 2010), and aircraft class contributions to airport noise exposure (Bernardo et al. 2017). As for emissions from aircraft operations, AEDT calculates pollutants emitted from an aircraft's main engines and emissions from auxiliary power unit (APU) which are typically found on large commercial aircraft. APU differ from aircraft to aircraft.

To model aircraft operations, I first specified the layout of LAX, which includes the location of its four runways, the locations of its 132 gates and 17 taxiways. I then entered aircraft operational data which include operation type (e.g., departure, arrival), date and time of aircraft movements, aircraft model, engine model, runway, flight route, and gate. Since TFMSC does not have aircraft flight route and gate data, I evenly distributed aircraft arrival and departure data from TFMSC to three arrival flight routes and three departure flight routes generally used for westerly operations (Figure 9). This is the general practice of air traffic controllers in order to avoid long queue by using any available flight tracks to new arrivals.

When dealing with gate assignment, I evenly distributed flights to the gates of the Tom Bradley international terminal for international passenger aircraft. Likewise, I distributed domestic passenger aircraft to the gates of the other eight terminals. Because LAX handle a large of freight every day, I treated cargo aircraft and military aircraft separately because both of them have a specific operational area. In general, military aircraft account for only a minor shares of aircraft operations at LAX.

Assignment of gate for each aircraft is not publicly available. In AEDT, gate assignment is a manual task, so it is impractical to assign gates in a one-year simulation. As mentioned above, I grouped aircraft into domestic and international flights and evenly distributed them to designated terminals and gates for domestic and international aircraft.

Ground support equipment (GSEs) is another substantial source of various air pollutant at airports and different aircraft types require a different configuration of GSEs. For $PM_{2.5}$, the impact of GSEs is notable (Yim et al., 2013). However, their impact area is smaller than the impact area of a commercial aircraft (Unal et al., 2005). Emissions are determined by GSEs type (e.g., air conditioner, baggage tractor) and by fuel type. I used default aircraft-assigned GSEs from AEDT to calculate emission inventory from GSEs.

I then defined the spatial scope of emissions to be included. For ground-based sources, the spatial scope is the area within the airport fence line. This is different from the geographic scope of receptor locations (discussed in the next section) for airborne aircraft emissions, which extends as far as 24 km from the airport and includes public, residential, and commercial areas. I also specified a vertical limit of 3,000 ft feet as my atmospheric mixing height which bounds the spatial scope of emissions sources vertically.

Gas emissions in AEDT were obtained from the International Civil Aviation Organization (ICAO) Aircraft Engine Emissions Databank, which contains mode-specific emission factors (EFs) for engines. Moreover, PM emissions are based on the First Order Approximation 3.0A (FOA3A) (Wayson et al., 2009). Standardized sampling techniques to measure volatile and nonvolatile PM emissions from aircraft engines do not exist. As such, a first-order approximation (FOA) was developed by the FAA to fill this gap based on available information. FOA1.0 only predicts nonvolatile PM and FOA2.0 includes volatile PM emissions on the basis of the ratio of nonvolatile to volatile emissions. FOA3.0 disaggregated the prediction techniques to allow for independent prediction of nonvolatile and volatile emissions on a more theoretical basis (Wayson et al., 2003; 2009).

When dispersing air pollutant emissions, AEDT will automatically generate hourly emissions files that can serve as inputs for AERMOD, an air quality dispersion model. After running Los Angeles International Airport operations for year 2014, I entered spatially resolved emission inventory profiles containing the time-varying emissions for each hour into AERMOD, which is embedded into AEDT2d but operates independently.

4.8 Air quality dispersion modeling (AERMOD)

As mentioned above, to disperse air pollutants emitted by aircraft and ground equipment, and to simulate atmospheric chemistry, I used the U.S. Environmental Protection Agency's (EPA) AERMOD model. AERMOD is a steady-state dispersion model designed for estimating the short-range dispersion of air pollutant emissions over a maximum of 50 km. Planetary boundary layer (PBL) is important in emission dispersion studies because PBL is the closest turbulent air layer to the earth surface and it is controlled by surface heating, friction and the overlying stratification. The PBL typically ranges from a few hundred meters in depth at night to 1 - 2 km during the day.

The AERMOD modeling system consists of two pre-processors: AERMET and AERMAP. Before running the dispersion model, AERMET processes meteorological data and AERMAP processes terrain data.

The primary purpose of AERMET is to provide AERMOD with the meteorological information it needs to characterize the PBL. Three meteorological datasets were preprocessed using AERMET: (1) standard hourly surface data in (ISHD) format; (2) 1-minute automated surface observation systems (ASOS) data in (DAT) format; and (3) the upper air sounding (radiosonde) data in (FSL) format. I used 1-min ASOS data[1] and hourly surface observations[2] collected from an on-site measurement at LAX and twice-daily upper air soundings[3] collected at the Marine Corps Air Station in Miramar by the National Weather Service (NWS). Two types of meteorological data files provided by the AERMET meteorological preprocessor are inputs to AERMOD. One file consists of surface scalar parameters, a file of hourly boundary layer parameter estimates (.sfc file), and the other file consists of vertical profiles of meteorological data, a file of multiple-level observations of wind speed and direction, temperature, and standard deviation of the fluctuating components of the wind (.pfl file) (EPA, 2018).

The terrain preprocessor (AERMAP) characterizes the terrain and generates receptor grids for the dispersion model. AERMAP preprocess terrain elevations data from the National Elevation Dataset (NED) developed by the U.S. Geological Survey (USGS, 2002). I downloaded Los Angeles terrain data from the Multi-Resolution Land Characteristics (MRLC)[4] consortium in GeoTIFF format and entered it into AERMAP. The LA terrain data covers a 90 km by 90 km area which includes all terrain features that exceed a 10% elevation slope from any given receptor required by AERMAP.

When creating flight routes in AEDT, the trace path of the flight trajectory is a 3-dimensional line. Flight tracks are defined as vector-type tracks (consisting of one or more straight or curved segments) to represent aircraft turning points. While in AERMOD, it is a corresponding line source., AERMOD is capable of handling multiple sources, including point, volume, area, and line sources (EPA, 2019). The line source algorithm is from the Buoyant Line and Point Source (BLP) model (Schulman and Scire, 1980). Therefore, the emissions during landing and takeoff were calculated using the BLP model.

The major features of the BLP dispersion model are: UTM or line source oriented coordinate system; multiple point source and finite buoyant line source capability; finite buoyant line source plume rise, plume enhancement due to multiple line sources; vertical wind shear in plume rise formulations for both point and line sources; transitional plume rise; incorporation of building downwash in both dispersion and plume rise calculations for point and line sources; terrain adjustment plume path coefficients; time-dependent pollutant decay; source contribution concentrations; and flexible post-processing package (OSTI, 1980).

I used grid receptors to capture the dispersion pattern of aircraft emissions. Emission dispersion computations require information about receptor locations. The receptor locations for a grid are defined by setting a starting point for the location of the lower-left corner of the Los Angeles International Airport (Latitude: 33.863167, Longitude: -118.472851), the number of grid points in the directions (X-axis: 150, Y axis: 50) and the distance between grid points in the same two directions (X-axes: 370 meters, Y axes: 370 meters). Consequently, I have a total of 7,500 receptors on a rectangular grid that is 55.5 kilometers long and 18.5 kilometers wide (Figure 22 and 23).

When running an emissions dispersion metric result function, AEDT will automatically invoke AERMOD, along with the appropriate meteorological and terrain data as inputs, to generate the dispersion results for each receptor.

Ambient concentrations for a pollutant are concentration measurement for that pollutant after it has been emitted from a source and mixed in the atmosphere (Beychok, 2005). For airport studies, the three key source categories are emissions from airport activities, emissions from other anthropogenic sources (nearby or long-range transport), and emissions from natural sources.

Likewise, AEDT models airport-related activities; therefore, the other two source categories must be added to estimate total ambient concentration (e.g., by adding mobiles' emission inventory from EPA's MOVES). The concentration added from non-airport sources is usually referred to as the background concentration. During airport evaluations, background concentrations, are estimated either from local monitoring stations or from a model. These concentrations should be directly comparable to the National Ambient Air Quality Standards (NAAQS) (Ahearn et al., 2016).

In this study, I treated ambient concentrations as constant (exogenous) for two reasons. First, I am interested in the air quality improvements caused by a congestion fee and its impacts on selected health outcomes (e.g., work loss days).

Second, the Concentration–response functions (C-R functions) that I used are linear or quasi-linear curves. Among various statistical methods used to assess the associations between exposure to ambient air pollution and health outcomes, the C-R functions is very popular. Otherwise, if the C-R functions are not linear or quasi-linear relationship, the difference would be large if we look at total concentration vs. airport-related concentrations in health outcomes. If that is the case, a background concentration should be included in health outcome estimation.

[1] ftp://ftp.ncdc.noaa.gov/pub/data/asos-onemin

[2] ftp://ftp.ncdc.noaa.gov/pub/data/noaa

[3] https://ruc.noaa.gov/raobs/

[4] https://www.mrlc.gov/tools

Chapter 5 Methodology and data for estimating health impacts

5.1 Introduction

The uncertainty of an assessment is related to a lack of knowledge about one or more components of the assessment (US EPA, 2011). In this chapter, I will start by discussing how health impacts (benefits) were estimated. The key parts of health outcomes modeling are population estimates, population exposure, health impact function, and the value of a statistical life (VSL). Second, I will conduct an extensive sensitive analysis from different engines used by the same aircraft and from the value of a statistical life (VSL) on fuel consumption and emissions reduction.

5.2 Health outcomes modeling (BenMAP)

Exposure to $PM_{2.5}$ from transportation, including aviation, is associated with an increased risk of in premature mortality (Arunachalam et al., 2011). Improvements in ambient air quality generally lower the risk of developing an adverse health effect by a fairly small amount across a large population (U.S. EPA, 2019a); a lower risk means that we can expect fewer cases of the adverse health effect considered. Several software tools exist to estimate the health and the economic value of avoided health effects associated with air quality changes; a list of software tool is shown in Table 3.

To assess conduct a benefit-cost analyses of air pollution control policies and how changes in human exposure to $PM_{2.5}$ concentrations affect selected health outcomes, I used the U.S. EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) because it has developed for studying continental U.S. and has a long history of application. Voorhees et al. (2011) quantify heat-related human health morbidity and mortality risks from climate change. Previous air pollution studies also use BenMAP to estimate health benefits of reducing air pollution in Shanghai (Voorhees et al., 2014) and of reducing $PM_{2.5}$ in China (Chen et al., 2017). San Jose et al. (2018) studied the health impact assessment of traffic restrictions on traffic parking and access restrictions. BenMAP uses a health impact function approach to estimate the health benefits of a change in air quality. The major components of the approach are population estimates, population exposure, adverse health effects, and economic costs.

The health effect estimate is an estimate of the percentage change in the risk of an adverse health effect due to a one-unit change in ambient air pollution (EPA, 2017a). When estimating leading causes of $PM_{2.5}$ -related premature mortality, hospital admissions and impacted days, I prioritize to use epidemiological studies available from the U.S. should be used. I made an exception for mortality from lower respiratory infection and cerebrovascular of mortality causes. For the two diseases cause of death estimation health outcomes, I relied on the integrated exposure-response functions (IERs) (Cohen et al., 2017) to estimate the relative risk of mortality of ambient annual mean $PM_{2.5}$ concentrations because IERs uses cause of death to estimate the relative risk of mortality over the entire global range from studies of ambient air pollution, household air pollution, and second-hand smoke exposure and active smoking. All concentration-response for mortality, hospital admissions and impacted days is are shown in Table 3.

Table 3. Assessment tools for air pollution health impact

Tool	Developing institution	Geographical scope	Health endpoint addressed
AirCounts	Abt Associates	Global (42 cities, additional 3000 under development)	Mortality
AirQ+	World Health Organization	Any population with a specified size, mortality and morbidity characteristics	Mortality and morbidity
Aphekom	French Institute of Public Health Surveillance	Global (current version focuses on Europe)	Mortality and morbidity
Economic Valuation of Air Pollution (EVA)	Aarhus University	Northern hemisphere, continental (e.g. Europe), national, city	Mortality and morbidity
EcoSense	University of Stuttgart	Europe	Mortality and morbidity
Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE)	US Environmental Protection Agency	Continental USA and China predefined; any other as defined by the user	Mortality and morbidity
Environmental Burden of Disease (EBD) Assessment tool for ambient air pollution	World Health Organization	Global	Mortality and morbidity
GMAPS	World Bank	Global	Mortality and morbidity
IOMLIFET	Institute of Occupational Medicine		Mortality and morbidity

SIM-Air	Urban emissions	Asia, Africa, Latin America	Mortality
TM5-FASST	European Commission Joint Research Centre	Global (56 source regions)	Mortality and morbidity

1. Morbidity may include cardiovascular diseases, respiratory diseases, hospital admissions, emergency room admissions, days of restricted activity, and work loss days. Not all tools address all morbidity outcomes.
2. Source: World Health Organization (2016), updated by the author.

Table 4. Selected C-R functions for mortality, hospital admissions & impacted days

Health endpoint	Authors	Study Location	Age range	Other Pollutant
Mortality				
Ischemic heart disease	Krewski et al. (2009)	116 U.S. cities	30-99	TSP, O_3, SO_4, SO_2
Lung cancer	Krewski et al. (2009)	116 U.S. cities	30-99	TSP, O_3, SO_4, SO_2
Lower respiratory infection	Cohen et al. (2017)	Global	30-99	O_3
Cerebrovascular disease	Cohen et al. (2017)	Global	30-99	O_3
All cause	Krewski et al. (2009)	116 U.S. cities	30-99	TSP, O_3, SO_4, SO_2
Hospital admissions				
Chronic lung disease	Moolgavkar (2000)	Los Angeles, CA	18-64	
Chronic lung disease	Moolgavkar (2003)	Los Angeles, CA	65-99	
Asthma	Sheppard (2003)	Seattle, WA	0-64	
Acute myocardial infarction	Zanobetti et al (2009)	26 U.S. Communities	18-99	
All respiratory	Zanobetti et al (2009)	26 U.S. Communities	65-99	
Impacted Days				
Work loss days	Ostro (1987)	U.S. contiguous	18-64	

Note: “C-R" stands for “concentration-response”.

BenMAP performs spatial and temporal calculations based on differences in air pollution concentrations between a baseline and a control scenario. My baseline scenario reflects 2014 air quality conditions, and my control scenario reflects air quality conditions after the implementation of a congestion fee.

5.3 Data

BenMAP requires data including population data, grid definitions, pollutants, baseline and control data, incidence and prevalence rates, health impact functions, inflations rates, and valuation functions. Population estimates data are from the United Nations Socioeconomic Data and Applications Center (SEDAC) with a 10 km × 10 km resolution. They were extracted from the BenMAP regional datasets (U.S. EPA, 2017c).

To estimate changes in health incidence, the first step is to calculate the change in $PM_{2.5}$ concentrations for a policy scenario, such as an air quality improvement produced by airport congestion fee. Baseline disease incidence data was also from the BenMAP regional datasets. Both population and disease incidence data have 38 unique gender-age groups with 19 age groups (<1, 1-4, …, 80-84, 85+) by two gender groups (male, female). The total population in the impact zone is 10.6 million (Figure 9). Health effect estimates were estimated for two $PM_{2.5}$ metrics (98^{th} percentile 24-hour concentration, and annual), as suggested by National Ambient Air Quality (NAAQ) Standards (NAAQ, 2018b).

Health impact functions calculate the change in the number of adverse health effects among the population associated with a change in exposure to air pollution. A typical health impact function has inputs specifying the pollutant; the metric (daily, seasonal, and/or annual); the age, race, ethnicity, and gender of the population affected; and the incidence rate of the adverse health effect (US EPA, 2017a).

Epidemiological studies document how pollutant concentrations impact the incidence of a variety of health outcomes. In this study, I use a dose-response parameter derived from several health impacts studies conducted in the U.S. and the world (Table 4) to estimate how changes in $PM_{2.5}$ concentrations affect the all-cause mortality, hospital admissions and work loss days incidence. Finally, by multiplying the change in incidence by the population to estimate the total cases or units avoided from imposing an airport congestion fee.

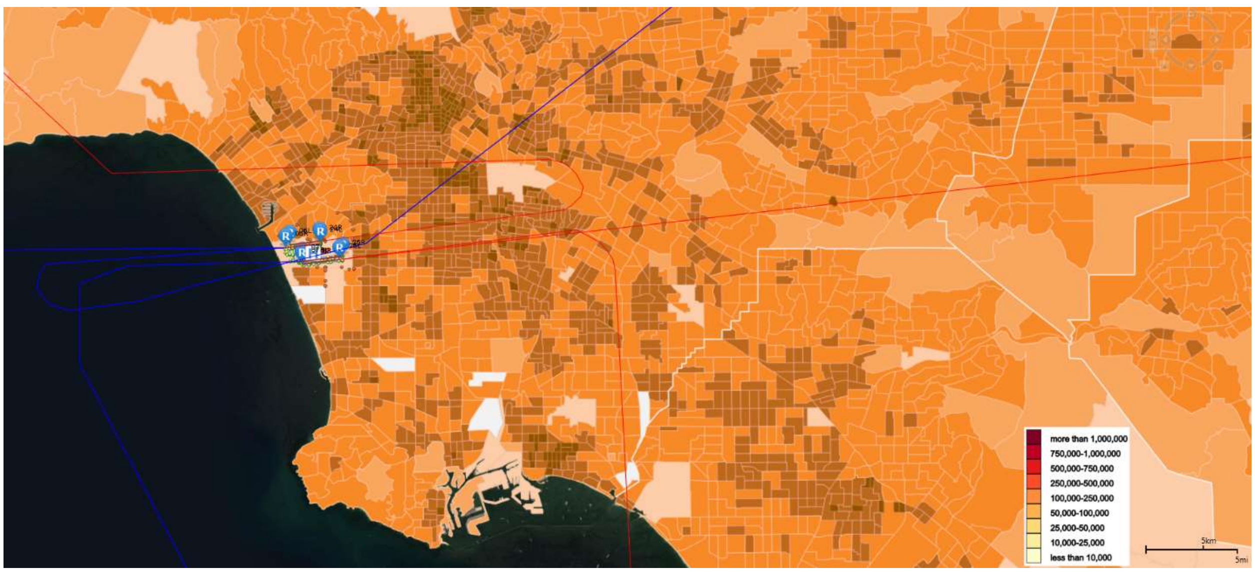


Figure 9. Population density and flight routes

Source: ESRI

Note: R represents runway ends; blue tracks represent departure routes and red tracks represent arriving routes.

5.4 Monetizing health outcomes

Monetizing the benefits of a reduction in air pollution involves estimating society's willingness to pay (WTP)[5] for these reductions in risk and the value of a statistical life (VSL), or the more accurate term "value of mortality risk reduction" which is the value of an avoided premature mortality.

The value of a statistical life is the monetary value that a group of people is willing to pay to slightly reduce the risk of premature death in the population. Because changes in individual fatality risks resulting from environmental regulation are typically minimal, the VSL approach is usually acceptable for these types of benefit analyses (U.S. EPA, 2019a). To calculate the value of a statistical life (VSL) for the U.S. in 2014, I used a VSL of $9.2 million as recommended by the U.S. Department of Transportation (2014).

5.5 Sensitivity analysis

Several of the input parameters used in this study are not known with great certainty and associated with uncertainties and they impact the results. They include uncertainties from the weather, major aircraft technical issues, the aircraft engine type, $PM_{2.5}$ emissions, type of social cost of carbon (SCC), the choice of concentration and response (C-R) function and value of a statistical life (VSL) based on my review of the existing literature, so I selected three of for my sensitivity analysis: aircraft engine type, social cost of carbon (SCC) and concentration and response (C-R) functions.

5.5.1 Aircraft engine type

I first analyzed the uncertainty from different aircraft engine type used for each aircraft model. Since airlines can choose different engines for the same aircraft model, it is a source of uncertainty for environmental impacts. For example, airlines can choose engines between General Electric/GEnx-1B and Rolls-Royce/Trent 1000 for their new Boeing 787-800 order during procurements. This will, in turn, affect the fuel consumption and the emissions of air pollutants resulting from the operation of that aircraft.

The literature on fuel consumption during aircraft landing and takeoff (LTO) is limited (Mazaheri et al, 2008). I compiled data for aircraft LTO fuel consumption rate with different engine types in order to conduct fuel and emission sensitivity analysis. The following steps were used to compile the aircraft LTO fuel burn rate, which is the number of kg of fuel burn each minute for an aircraft:

- I first reviewed the average monthly aircraft operation in LAX and picked the aircraft most flown (Figure 10).
- From each aircraft manufacturer's documentation, I found all engine types that could be used on these aircraft; and
- I matched the engine types with the data from the International Civil Aviation Organization (ICAO) emission databank (2019).

Table 5 shows the fuel burn rate for the 32 most commonly aircraft at LAX. It includes the upper and the lower bounds of aircraft fuel consumption for different engines. In general, newer models consume less fuel during the LTO cycle. For example, the old version of Boeing 737-800 burns 25.0 - 27.7 kg of fuel per minute, while the new Boeing 737-MAX 8 burns 20.1 - kg of fuel per minute. Likewise, the Boeing 747-400 and Boeing 777-200 are both popular models for international long-haul flights. The Boeing 747-400 burns 123.5 - 160.7 kg of fuel per minute, while the Boeing 777-200 burns 67.9 - 89.9 kg of fuel per minute (Table 5).

Before conducting the fuel save and emission reduction sensitive analysis, I took the lower-bound of the fuel consumption rate in LTO cycle for each aircraft type and applied them to the LAX operations in AEDT. AEDT allows assigning different engines to a specific aircraft type, which I did to obtain both lower and upper bounds for aircraft emissions. I then used AERMOD to generate lower-bound for $PM_{2.5}$ emissions for dispersion. The lower-bound $PM_{2.5}$ emission is used to further analyze the improved air quality before and after imposing an airport congestion fee. Likewise, the upper-bound of the fuel consumption rate in the LTO cycle of aircraft was used to analyze the improved air quality from an airport congestion fee. The results of the engine-type sensitive analysis for both fuel saved and $PM_{2.5}$ change can be found in Table 6 in the next chapter.

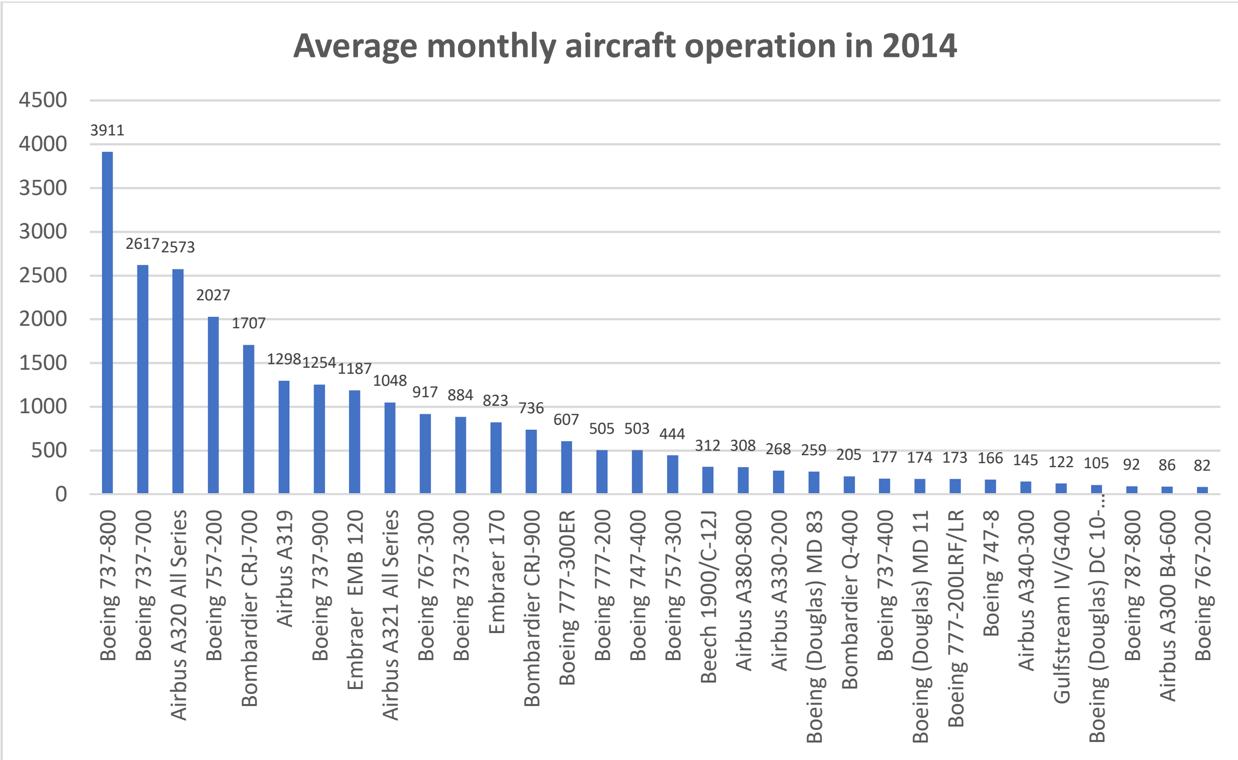


Figure 10. Aircraft portfolio of LAX

Source: TFMSC (2014)

Table 5. Fuel consumption rate for LTO cycle

Aircraft type or series	Engine Manufacture/ Types	Number of Engines	Fuel consumption rate in LTO cycle (kg/minute)
Boeing 737-800	CFM International / CFM 56-7B24, 26, 27	2	25.0 - 27.7
Boeing 737-700	CFM International / CFM 56-7B20, 22, 24, 26, 27	2	21.9 - 27.7
Airbus A320 All Series	CFM International / CFM 56-5B International Aero Engines/ IAE V2500A5	2	26.9 - 28.8
Boeing 757-200	Rolls-Royce/ RB211-535E4(B), Pratt & Whitney PW2000-37, 40, 43	2	33.3 - 38.4
Bombardier CRJ-700	General Electric/ CF34-8C5B1	2	14.0
Airbus A319	CFM International / 56-5B, Pratt & Whitney/ PW6000A	2	18.4 - 24.4
Boeing 737-900	CFM International / CFM 56-7B24, 26, 27	2	25.0 - 27.7
Embraer EMB 120	Pratt & Whitney PW118, 118A, 118B	2	18.4 - 22.8
Airbus A321 All Series	CFM International/CFM56-5B International Aero Engines/ IAE V2500A5	2	24.7 - 28.8
Boeing 767-300	Pratt & Whitney/ PW JT9D, 4000 General Electric/ CF6-80	2	43.1 - 48.8
Boeing 737-300	CFM International/ CFM56-3B-2	2	25.6
Embraer 170	General Electric/ CF34-8E	2	13.7
Bombardier CRJ-900	General Electric/ CF34-8C5	2	14.6
Boeing 777-300ER	General Electric/ GE90-110B1,115B	2	89.9 - 94.0
Boeing 777-200	General Electric/ GE90, Pratt & Whitney/ PW4000, Trent 800	2	67.9 - 89.9
Boeing 747-400	PW/4000, GE/ CF6, Rolls-Royce/ RB211	4	123.5 - 160.7
Boeing 757-300	Rolls-Royce/ RB211-535E4(B), Pratt & Whitney/ PW2000-37, 40, 43	2	38.4 - 44.6
Beech 1900/C-12J	Pratt & Whitney/ PT6A-67D	2	4
Airbus A380-800	Engine Alliance/ GP7200, Pratt & Whitney/ Trent 900	4	113.3 - 122.7
Airbus A330-200	GE CF6, PW 4000, Rolls-Royce/ Trent 700	2	50.5 - 66.0

Boeing Douglas MD 82/ 83	Pratt & Whitney/ JT8D-200	2	28.5
Boeing Douglas MD 11	Pratt & Whitney/ PW4460,62 General Electric/ CF6-80C2D1F	3	51.4 - 55.8
Boeing Douglas DC 10-10/30/40	General Electric/ CF6-6D, CF6-50C Pratt & Whitney/ JT9D-59A	3	66.7 - 82.1
Bombardier Q-400	Pratt & Whitney/ PW150	2	18.2
Boeing 737-400	CFM International/ CFM56-3C-1	2	27.2
Boeing 777-200LRF/LR	General Electric/ GE90, Pratt & Whitney/ PW4000 / Trent 800	2	72.5 - 82.5
Boeing 747-8	General Electric/ GEnx-2B67	4	105.0
Airbus A340-300	CFM International/ CFM56-5C	4	56.7
Boeing 787-800	General Electric/ GEnx-1B, Rolls-Royce/ Trent 1000	2	51.9 - 56.0
Airbus A300 B4-600	CFM International /CF6-80C2, Pratt & Whitney/ PW4158	2	50.0
Boeing 767-200	Pratt & Whitney/ JT9D, PW4000, General Electric/ CF6-80, Engine Alliance/ RB211-524	2	45.8 - 48.8
Gulfstream IV/G400	Rolls-Royce Tay 611-8C	2	19.5
Boeing 737 MAX-8	CFM International LEAP-1B	2	20.1

5.5.2 Uncertainty analysis of health impacts

Lastly, I studied the uncertainty of the health benefit of congestion pricing. Following the method adopted by Stettler et al. (2011) of estimating health impacts of UK airports, I used Monte Carlo analysis to quantify the confidence intervals around mean incidence and the economic value estimated by randomly sampling an uncertainty distribution around the effect coefficients. I performed 100,000 iterations to obtain the associated distributions of modeling outputs. From this, summary statistics have been calculated with 95 confidence interval (2.5th and 97.5th percentiles) and are reported in Table 7.

I discuss the C-R functions used in this study in detail. Krewski et al. (2009) study a cohort consists of approximately 360,000 participants residing in areas of the country that have adequate monitoring information on levels of $PM_{2.5}$ for 1980 and about 500,000 participants in areas with adequate information for 2000. Three main analyses were conducted: a Nationwide Analysis, Intra-Urban Analyses in the New York City (NYC) and Los Angeles (LA) regions, and an analysis designed to investigate whether critical time windows of exposure to pollutants might have affected mortality in the cohort. Exposure was averaged for all monitors within a metropolitan statistical area (MSA) and assigned to participants according to their Zip Code area (ZCA) of residence.

BenMAP applies these functions to the baseline mortality rate and the number of people potentially exposed. BenMAP provides distributions of premature mortality estimates based on the uncertainty in the concentration-response functions. Monetized estimates of premature mortality are based on estimates of the value of mortality risk as defined by the U.S. EPA. This estimate is based on people's willingness to pay for reducing risk. Therefore, this estimate is not about a price on a life, but a price of risk reduction.

The value of a statistical life is more accurately referred to as the value of mortality risk. The U.S. EPA recommends a value of $9.4M in 2014 dollars.

Chapter 6 Results

The integrated modeling methodology described in the previous sections was developed to address two questions:

1. What are the air quality changes and health benefits of the airport congestion fee?
2. What are the impacts on congestion pricing of considering different social costs of carbon (SCC)?

The results for each question are presented sequentially, starting with airport traffic simulations, then air quality modeling, and lastly the health and climate benefits. To assess the climate impacts of GHG emissions, the global social cost of carbon (GSCC) and country-level social cost of carbon (CSCC) are presented for each scenario considered. To assess health impacts, $PM_{2.5}$ emissions are discussed, followed by air quality modeling and the human health benefits assessment of various changes in air quality.

6.1 Health benefits of the airport congestion pricing

Hourly airport operation and the resulting emissions for LAX were simulated for the entire year 2014. My baseline was no congestion fee and my control scenario is imposed airport congestion pricing that takes CO, NO_X, HC, SO_X and PM emissions into account. These pollutants are the most commonly pollutants found in the exhaust from jet engine and APU (Kinsey et al., 2012). I will first discuss improvement in airport traffic from a congestion fee and then present air quality, health, and climate changes.

The hourly airport operation and emissions from LAX were simulated for the entire 2014 year under baseline of no congestion fee and control scenarios of imposing airport congestion pricing which take CO, NO_X, HC, SO_X and PM emissions into account. These pollutants are the most common pollutants found in the exhausted air from jet engines and APU. I will first discuss the improvement of airport traffic from congestion fee and then air quality changes. Finally,

6.1.1 Improvement of airport traffic

Similar to free flow travel speed in highway traffic, the minimum taxi-out time of flights is the unimpeded taxi-out time, i.e. when aircraft do not encounter any congestion, bad weather, or other delay factors on the shortest taxi route from its gate to the runway (FAA[b], 2019).

In this section, I first analyze the unimpeded taxi-out time data of LAX provided by the FAA's Aviation System Performance Metrics (ASPM) database. As shown in Figure 11, the first airport traffic bottleneck for LAX is at 36 flights per hour. The aircraft traffic flow rate below 36 flights is similar to unsaturated traffic flow on the road. The region which represents unsaturated traffic conditions ($\lambda^t \leq 36$) is associated with uninterrupted airport traffic, where the taxi-out time remains stable and nearly constant. The unimpeded taxi-out time, defined as the time spent by an aircraft moving from its gate to the runway in free-flow travel speed, was computed as the average taxi-out time minus the taxi-out time delay in ASPM.

The second airport traffic bottleneck for LAX is at 54 flights per hour. Aircraft traffic flow between 37 and 54 flights per hour is akin to saturated traffic flows, where taxi-out time starts to increase with aircraft flow. If the aircraft flow rate is over 55 flights, it can be defined as over-saturated traffic where taxi-out time increases drastically. To the best of my knowledge, this is the first study that uses road traffic concepts (BPR function) to analyze airport congestion and traffic.

Any measure designed to alleviate congestion, either by demand or supply management, should try to avoid over-saturated traffic and manage to transition peak hours traffic to off-peak hours in order to increase the portion of unimpeded taxi-out time (free-flow travel speed) in the airport. In this study, I only implement a congestion fee at hours when saturated traffic and over-saturated traffic are present ($\lambda^t > 36$).

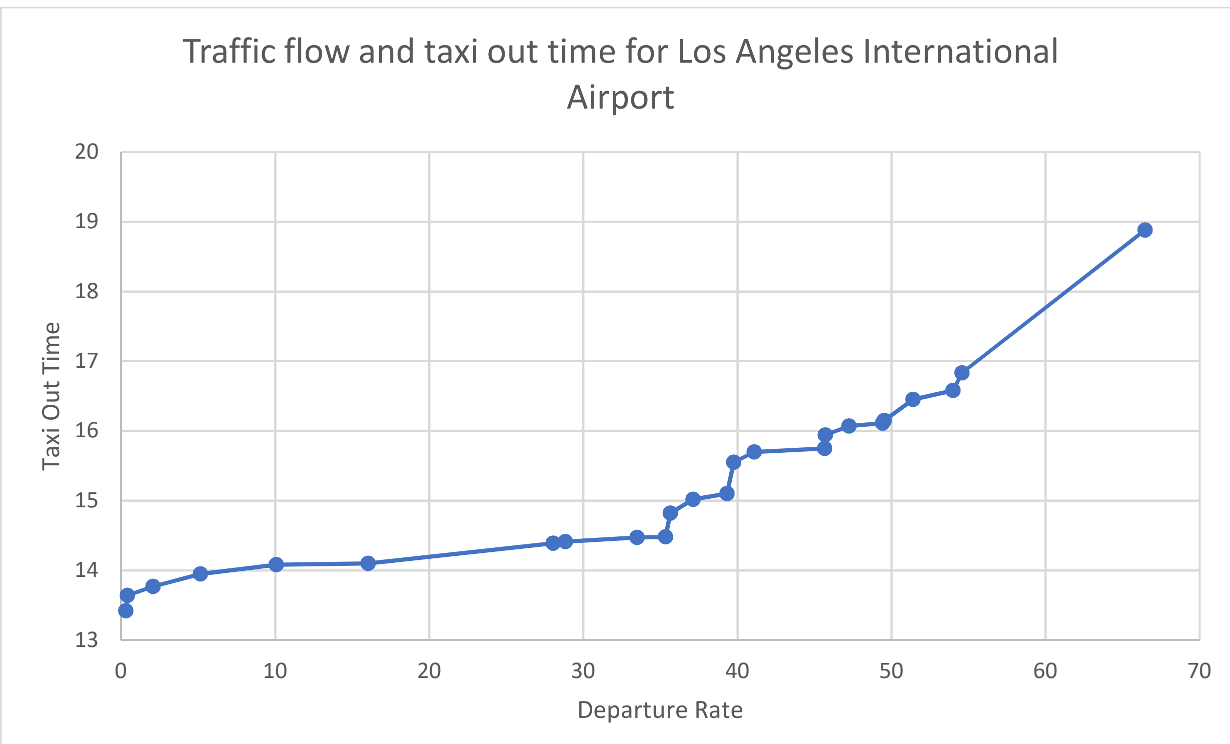


Figure 11. Taxi time as a function of flow rate

Figures 12 and 13 depict simulation results for no congestion fee and congestion fee equilibria. The figures show that congestion levels were greatly reduced by the pollutant-based congestion pricing, illustrating the importance of intertemporal substitution. Clearly, congestion pricing outperforms current weight-based airport fees, which are commonly in use.

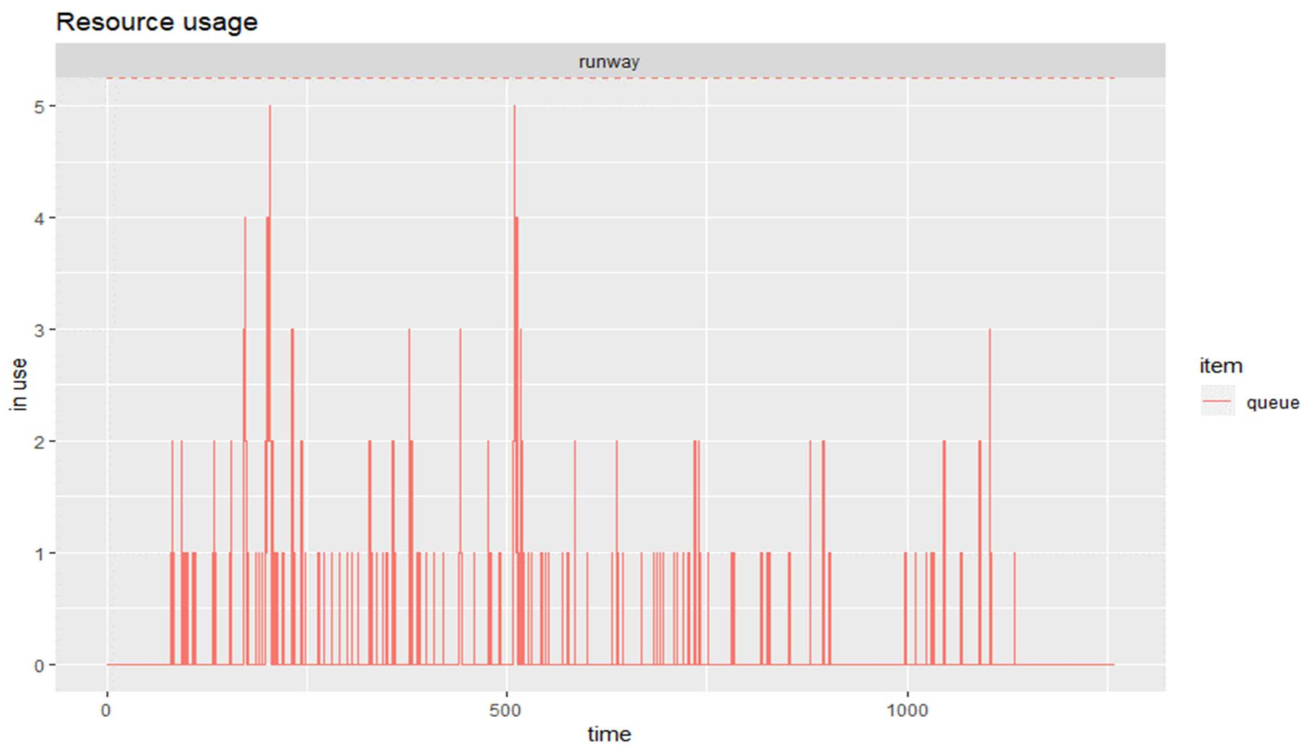


Figure 12. Number of flights in a queue (before congestion fee)

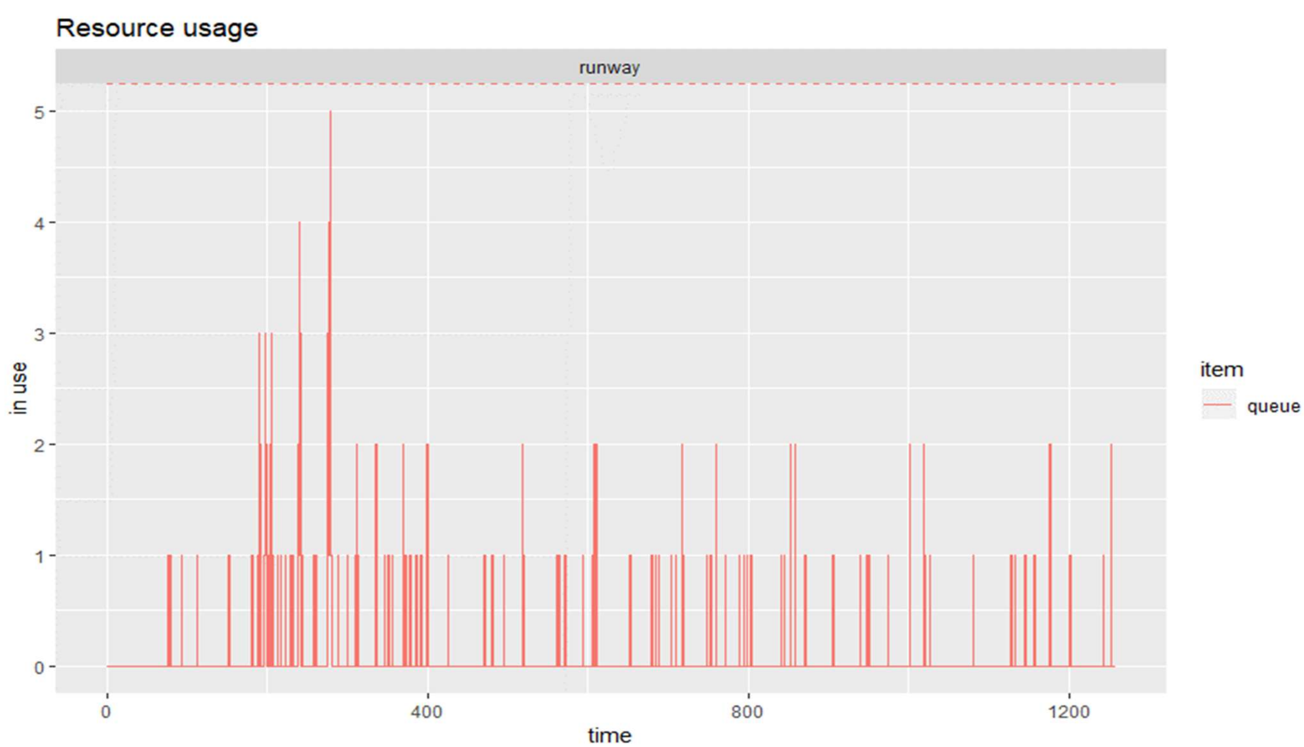


Figure 13. Number of flights in a queue (after congestion fee)

Specific congestion fees could be calculated for each hour and for each day of the month. However, this approach would be complex and cumbersome to implement, especially when it is first introduced. For simplicity and convenience, I propose instead hourly congestion fees for both peak and off-peak seasons.

In support of this approach, please note that there is no large difference in the number of flights between weekdays and weekends at LAX. The airport and airline manage to spread the traffic evenly throughout the week (Figure 14). In contrast, the number of flights at LAX exhibits strong seasonality. For LAX, the peak season is summer as June, July and August are among the busiest months (Figure 15).

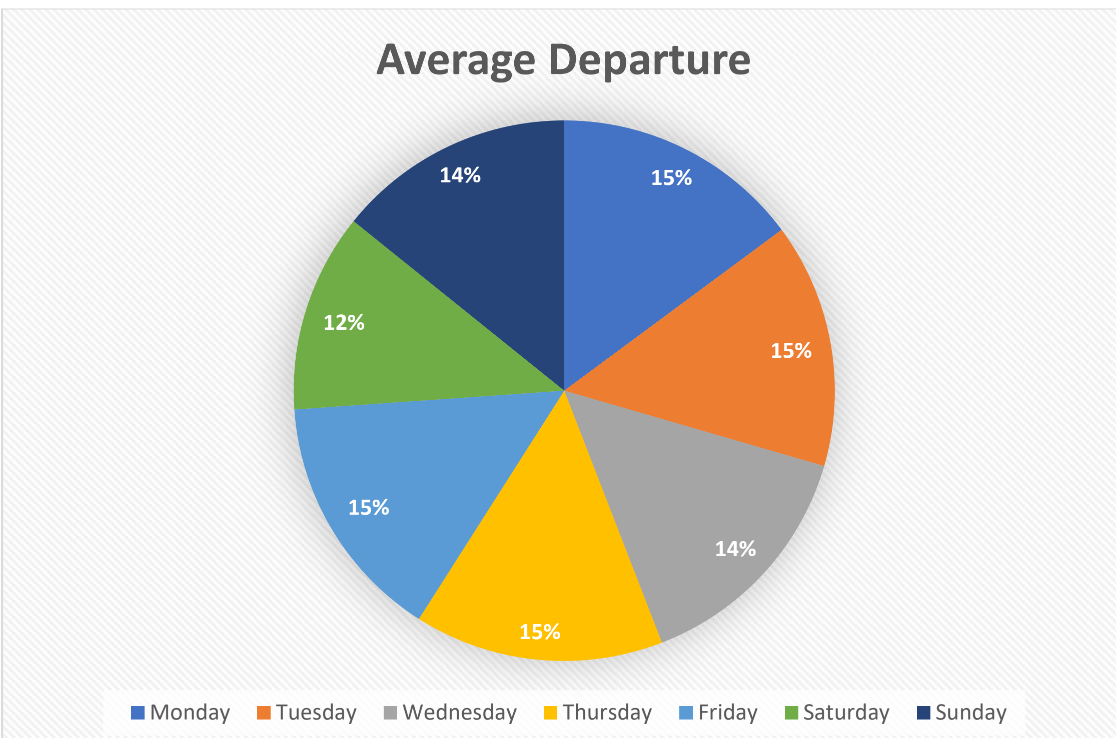


Figure 14. Average daily flights of LAX

Source: Airline Service Quality Performance System

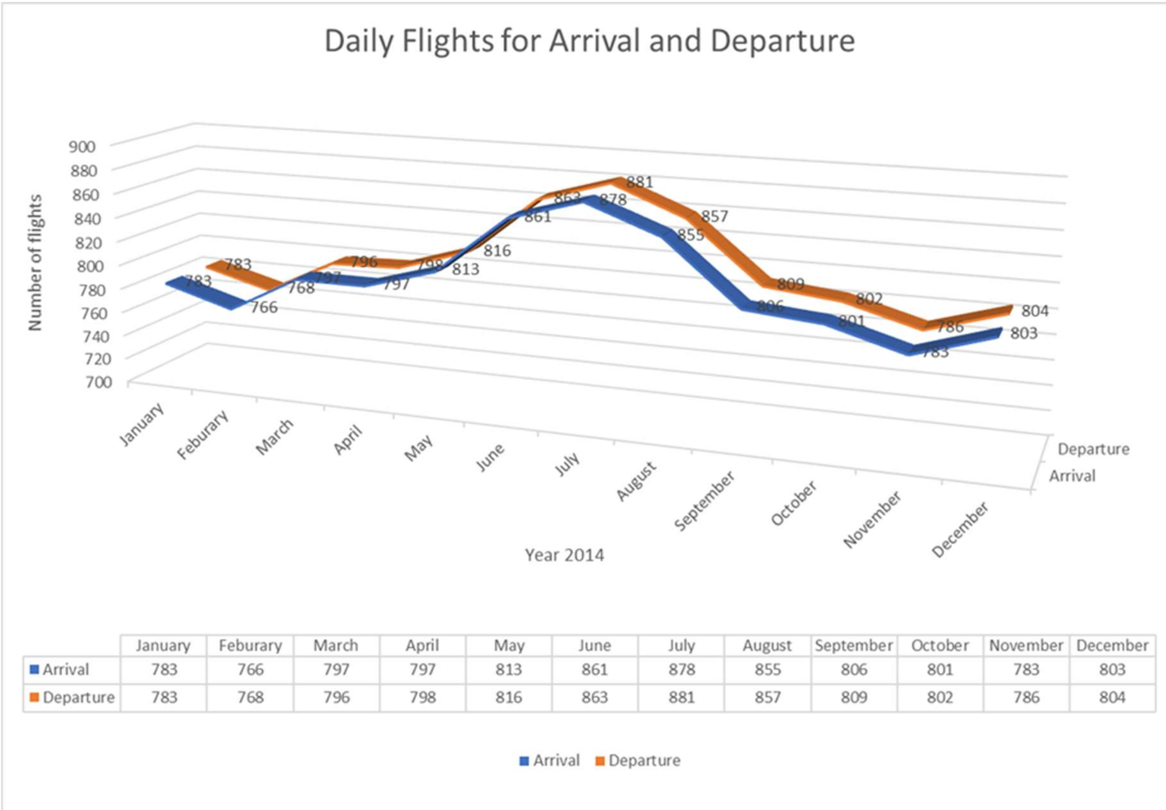


Figure 15. Average daily flights for arrivals and departures

Source: TFMSC (2014)

The underlying rationale of airport congestion fee is to set the congestion fee equal to the amount of external marginal cost. This will decrease the demand for airlines adding more flights at peak hours and will help spread out flights. Hence the new equilibrium of flights will be adjusted to the schedule where better social welfare is located.

The best scenario after imposing airport congestion fee is that all the scheduled flights in each time slot are within the first bottleneck, 36 flights per hour. However, in practice passenger demand in different flight time plays an important role. Therefore, in order to move all aircraft operating in unsaturated traffic condition, it is unlikely to spread all flights evenly solely by the congestion fee.

Figure 16 and 17 show that almost all the traffic in morning-peak hours move from the over-saturated region (over 55 flights per hour) to saturated traffic region where traffic flow is between 37 and 55 flights per hour. This reduced taxi queue and taxi-time and it solves the AM-peak congestion problem of LAX.

The airport congestion fee is valid when dealing with AM-peak traffic in both peak and off-peak seasons, especially for off-peak seasons. The congestion fee curbs the excessive demand in AM peak and successfully control the traffic rate well below the over-saturated threshold. However, like many others, the model is not perfect. Some of the flights scheduled in the morning were moved to 7 PM and 11 PM to avoid any congestion fee. This increases the traffic between 8 PM to 10 PM in off-peak seasons and moves traffic from unsaturated to saturated region (Figure 17).

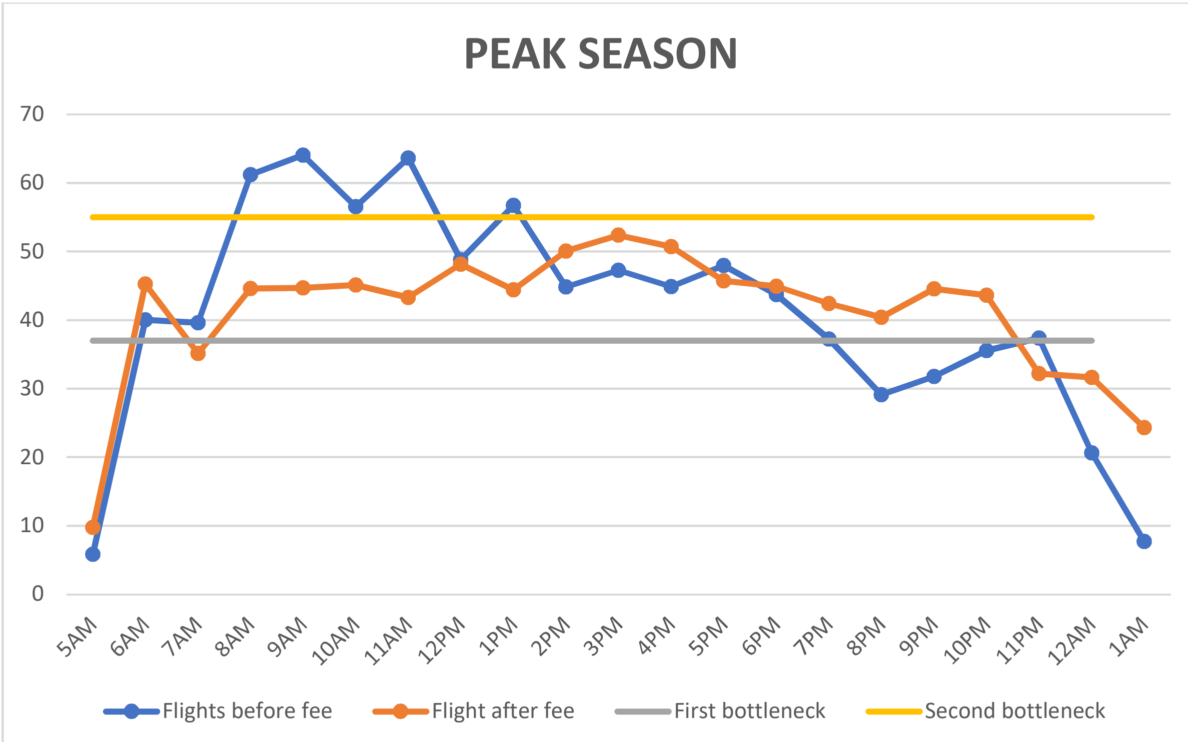


Figure 16. Airport traffic for peak season

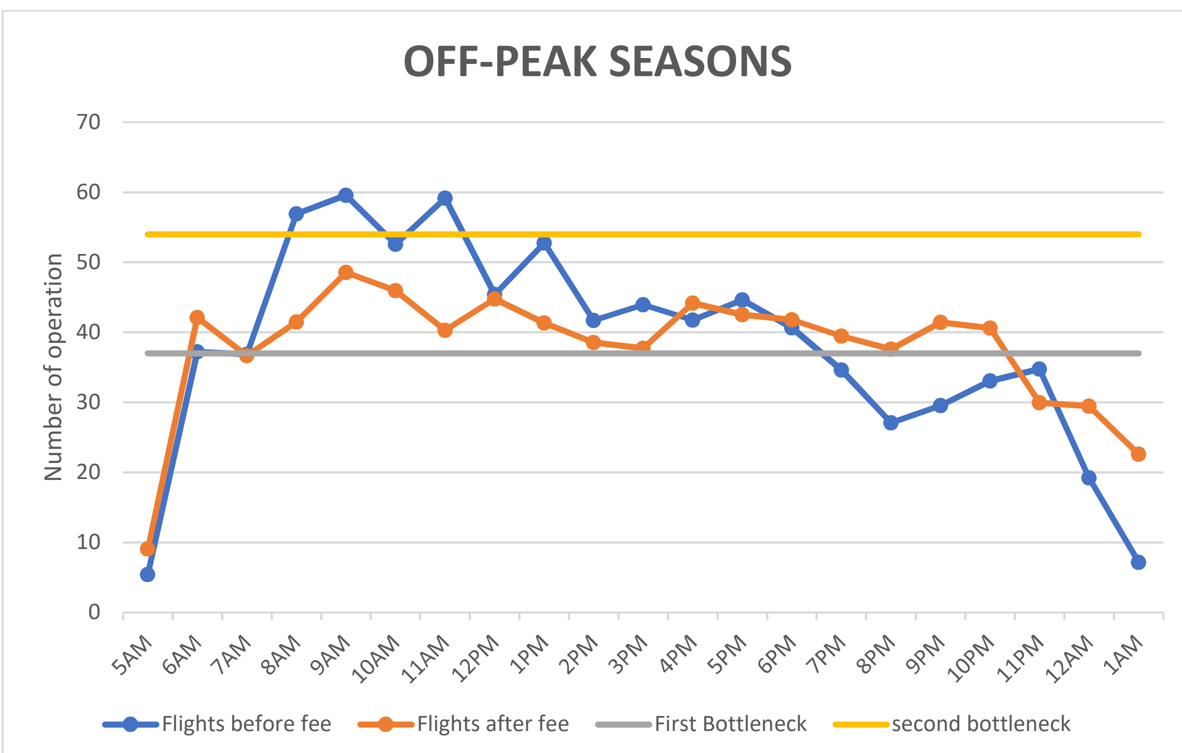


Figure 17. Airport traffic for off-peak seasons

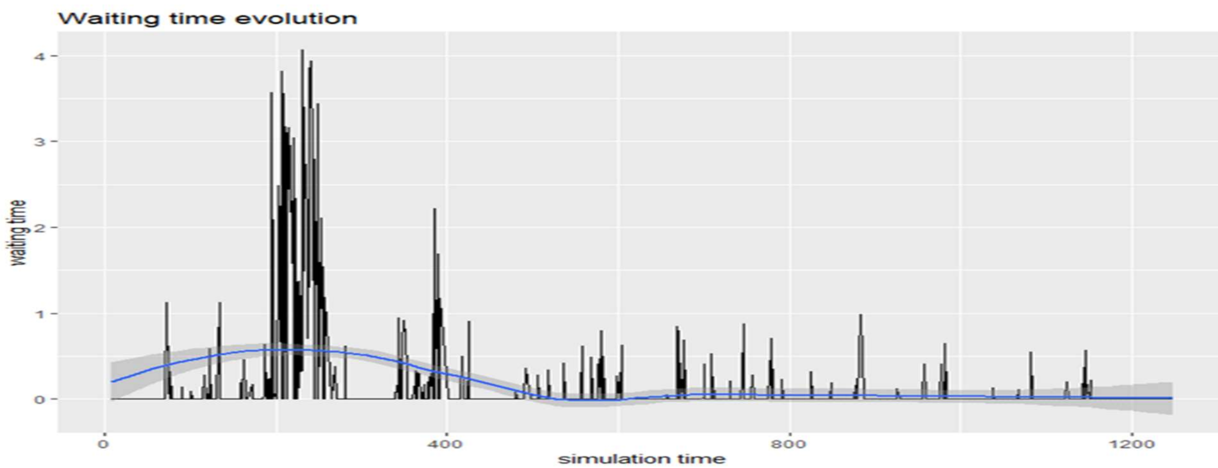


Figure 18.Individual and average waiting time for a runway in peak season

(before a congestion fee)

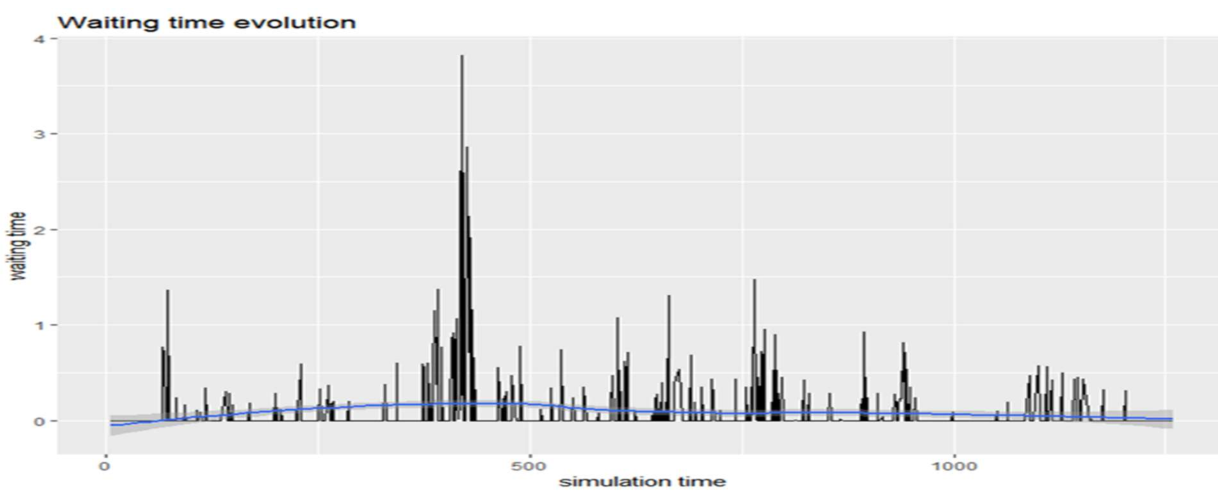


Figure 19. Individual and average waiting time for a runway in peak season

(after a congestion fee)

(Source: DES; Unit: minute)

6.1.2 Analysis of results from imposing the airport congestion fee

Simulation results from DES show that during the 1260-minute (5 am to 1 am next day) westerly operation, individual and average aircraft waiting time for a runway was reduced by the proposed congestion fee (Figure 18 and 19). It is another indication that the average runway waiting time (blue lines) in AM peaks has been reduced and overall runway waiting time variation is also reduced after imposing the congestion fee. Moreover, the frequency of spikes that represent prolonged runway waiting time is largely reduced. In Los Angeles, an analysis of health gains from implementing congestion pricing shows that an airport congestion fee is beneficial to the local environment and health, the results are presented in Table 7.

6.1.3 Air quality changes

As expected, the annual mean $PM_{2.5}$ concentration plots indicate that the highest concentrations are closest to the runway end and disperse east, according to the direction of the wind rose for Los Angeles International Airport in 2014. The 2014 wind rose for LAX, which displays the annual distribution of wind speeds and directions, are presented in the Figure 21. AEDT results were checked and no abnormal concentrations or wind patterns were detected. Figure 22 and 23 are the $PM_{2.5}$ dispersion from AEDT and they show the air quality improvement from the airport congestion fee.

Table 6. Air quality concentrations from aviation after AERMOD dispersion

Average annual mean of all grid cells ($PM_{2.5}$ μg/m^3)	Before the congestion fee	After the congestion fee	Percentage change
Peak season	3.1	2.7	-13%
Off-peak season	2.4	2.2	-10%

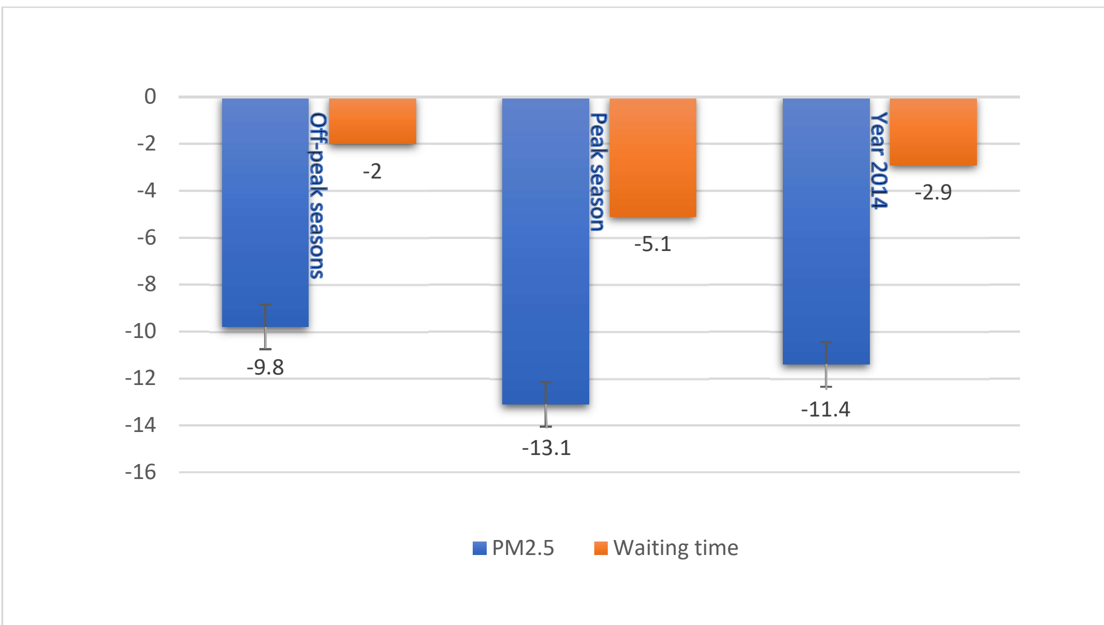


Figure 20. Reduction of $PM_{2.5}$ and average waiting time

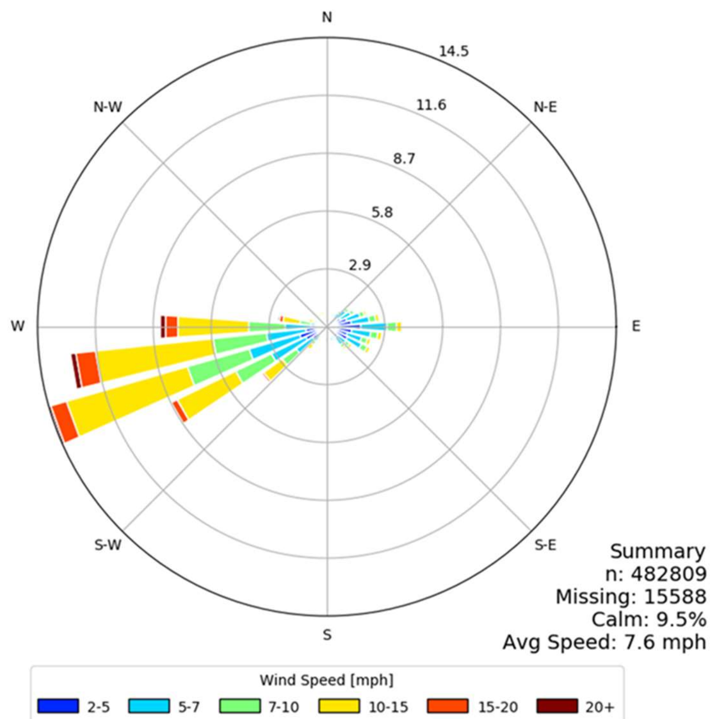


Figure 21. Windrose of LAX

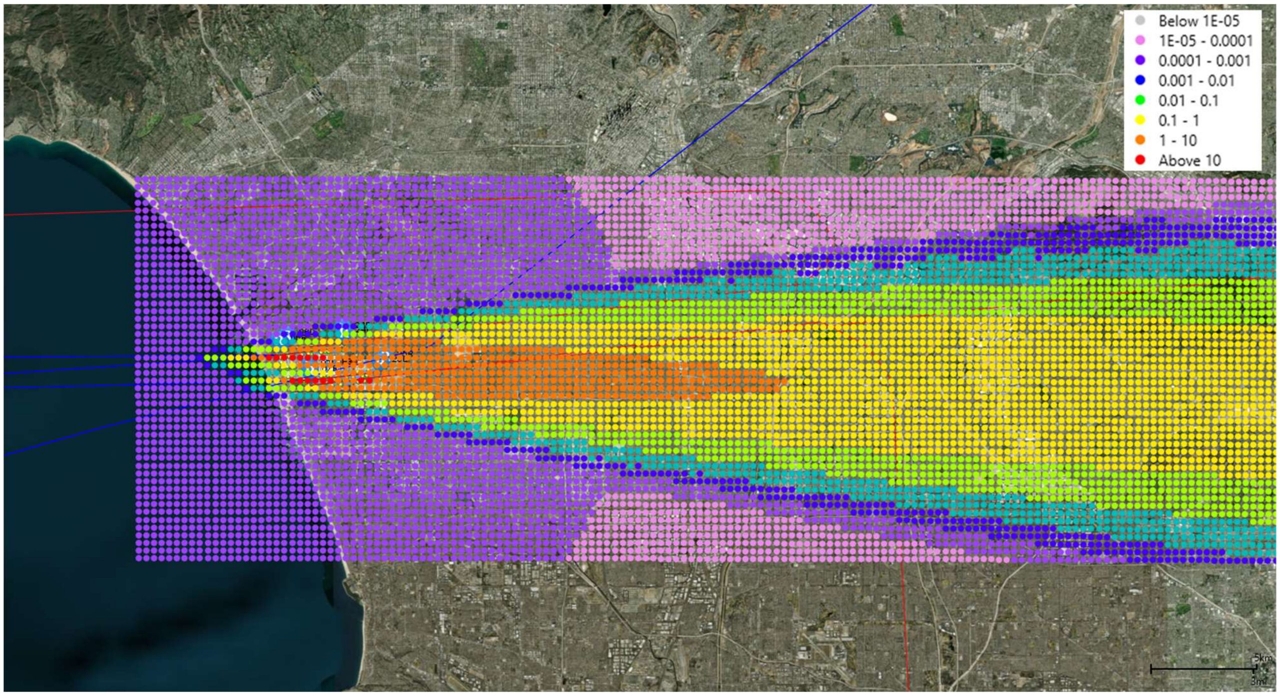


Figure 22. Dispersion of $PM_{2.5}$ (μg/m^3) before congestion fee

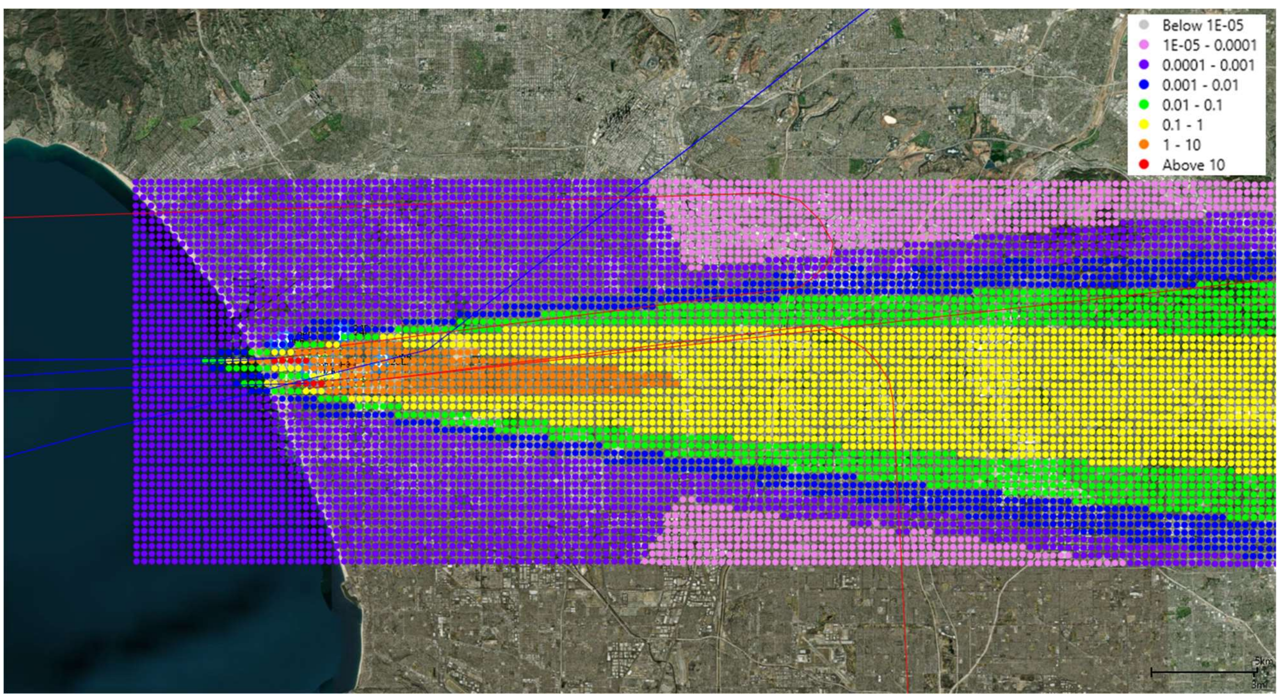


Figure 23. Dispersion of $PM_{2.5}$ (μg/m^3) after congestion fee

6.1.4 Human health impacts

Epidemiological studies have shown that long-term population exposure to $PM_{2.5}$ is associated with increased risk of health impacts including cardiovascular, pulmonary disease and premature mortality (Pope et al., 2002; Ostro, 2004; Künzli et al., 2005; Cooke et al., 2007; Roman et al., 2008). The health outcomes are presented in terms of changes in premature mortality and morbidity incidences, along with a monetary valuation of those changes in expected death, disease incidences and impacted days. Using BenMAP, I estimated the expected human health benefits from congestion fee with three different environmental costs scenarios for the aircraft operation at LAX: solely pollutants cost, pollutants cost with the country-level social cost of carbon (CSCC) and pollutants cost with global social cost of carbon (GSCC).

Implementing Scenario 1 and congestion pricing prevents a number of mortality and morbidity. Results from the Monte Carlo analysis for obtaining confidence intervals around health benefits from the congestion fee are showed in Table 7. The imposition of an airport congestion fee considering solely pollutants cost would reduce (1) premature mortality from $PM_{2.5}$ exposure by 4.6 cases (95 % CI: 3.1, 6) each year which have estimated monetary value 45.8 million (95% CI: 30.8, 59.7). (2) avoided hospital admissions for cardiovascular diseases by 167 cases (95 % CI: 71, 327) with estimated monetary value 21.9 million (95 % CI: 9.3, 42.8) (3) avoided hospital admissions for respiratory by 86 cases (95 % CI: 33, 140) with estimated monetary value 7.5 million (95 % CI: 2.9, 12.2) and (4) avoided work loss days by 8,539 units (95 % CI: 3,511, 13,247) with 1.4 million (95 % CI: 0.6, 2.1) monetary value (all in 2014 dollars).

Table 7. The economic valuation of health benefits from the airport congestion fee.

	Disease incidence (# reduction/year)	Health benefits (million US $2014/year)
Premature mortality, all causes	4.6	45.8
	(95 % CI: 3.1, 6)	(95% CI: 30.8, 59.7)
Hospital admissions,	167	21.9
cardiovascular	(95 % CI: 71, 327)	(95 % CI: 9.3, 42.8)
Hospital admissions, respiratory	86	7.5
	(95 % CI:33, 140)	(95 % CI: 2.9, 12.2)
Impacted Days, work loss days	8,539	1.4
	(95 % CI: 3,511, 13,247)	(95 % CI: 0.6, 2.1)

Definition of abbreviations: CI = confidence interval.

6.2 Health, climate benefits of congestion pricing with social cost of carbon

The social cost of carbon (SCC) is a first estimate of the Pigou tax that should be placed on carbon dioxide emissions (Tol, 2008). As Daniel (1995, 2000, 2009) concluded that airport congestion fee can spread out the traffic "bank" and reduce airport congestion. The social cost of carbon (SCC) is an important source of environmental externality of aviation activities. Even though aviation is the second-largest source of GHG emissions in the transportation sector, it was excluded from the recent COP21 Paris Agreement. I think taking aviation GHG emissions into energy and environment is the foremost issue policymakers have to address, Pricing GHG emission for airport congestion is a good start point.

US National Academies suggests the calculations of the social cost of carbon through a process with four distinct components (NAS et al., 2017): socio-economic module, climate module, damages module and discounting module. Here, I focused only on climate impacts use data from studies that are associated with climate impacts.

I start this section by calculating the global social cost of carbon (GSCC) of Landing and takeoff (LTO) and country-level social cost of carbon (CSCC) of LTO at LAX. The average LTO fuel-consumption rate of aircraft fleet at LAX is 35.76 kg per minute. It is calculated from multiplying fuel-burn rate for LTO cycle in Table 5 weighted by Aircraft portfolio of LAX in Figure 10.

As mentioned in Subsection 3.2.5, the International Civil Aviation Organization (ICAO) (2013) standard for transferring 1 kg of burning jet fuel to CO_2 is 3.16 kg CO_2 for each kg of fuel. Aviation CO_2 emissions are reported to the United Nations Framework Convention on Climate Change (UNFCCC) by a factor of 3.16 times the fuel amount (ICAO, 2013). The first step of calculating CSCC and GSCC is to multiple fuel consumption rate (kg/min) with Jet fuel to CO_2 ratio (3.16), the product is CO_2 emission per minute.

To calculate the global social cost of carbon (GSCC) of LTO, I multiple the amount of CO_2 emission per minute with EPA suggested \$36 per tonne (\$0.036 per kg) and the result is the CSCC of LTO and equal to \$4.07 per minute. Likewise, I multiple the amount of CO_2 emission per minute with the global social cost of carbon (GSCC) \$417 per tonne (\$0.417 per kg) and the result is the GSCC of LTO and equal to \$47.12 (Table 8).

Table 8. Social cost of carbon for LTO cycle

Fuel consumption rate (kg/min)	Jet fuel to CO_2 ratio	CO_2 (kg/min)	CSCC (US$/min)	GSCC/min (US$/min)
35.76	3.16	113.00	4.07	47.12

Note:
1. CSCC stands for country-level social cost of carbon and GSCC stands for global social cost of carbon.
2. CSCC: $36 per tonne ($0.036 per kg)
3. GSCC: $417 per tonne ($0.417 per kg)

Table 9. Comparison of pollutants cost and two social costs of carbon

	Pollutants cost only (percentage)	Pollutant cost + CSCC (percentage)	Pollutant cost + GSCC (percentage)
TDOC	65.23 (36%)	65.23 (35%)	65.23 (29%)
Pollutants cost	116.18 (64%)	116.18 (63%)	116.18 (50%)
CSCC	--	4.07 (2%)	--
GSCC	--	--	47.2 (21%)
Total LTO cost	181.41	185.47	228.53

Note: TDOC stands for total direct operation cost; all costs are based on US$ per minute.

6.2.1 Simulation results

Congestion pricing causes four types of traffic adjustment: sorting aircraft by time values, peak spreading, sorting by time preferences, and changing proportions of aircraft types (Daniel, 2001). Changing proportions of aircraft types is a long-term effect from demand management measures, it may take years for airlines to upgrade their fleets to newer and greener aircraft. My results conclude that, in the short run, congestion pricing can effectively spread out peak traffic.

In scenario 1, I applied a congestion fee which price solely on pollutants. The results were shown in Figure 24. The maximum congestion fee is $1,237 at 11 am and the minimum fee is $122 at 7 am while the median fee is $652 at 8am. There are two components that constitute the congestion fee, the first part is due to the cost of the pollutants (marked with orange color) and the second is due to the total direct operation cost (TDOC) (marked with grey color). TDOC accounts for 25% to 41% of total congestion fee while pollutant cost accounts for 59% to 76% of total fee.

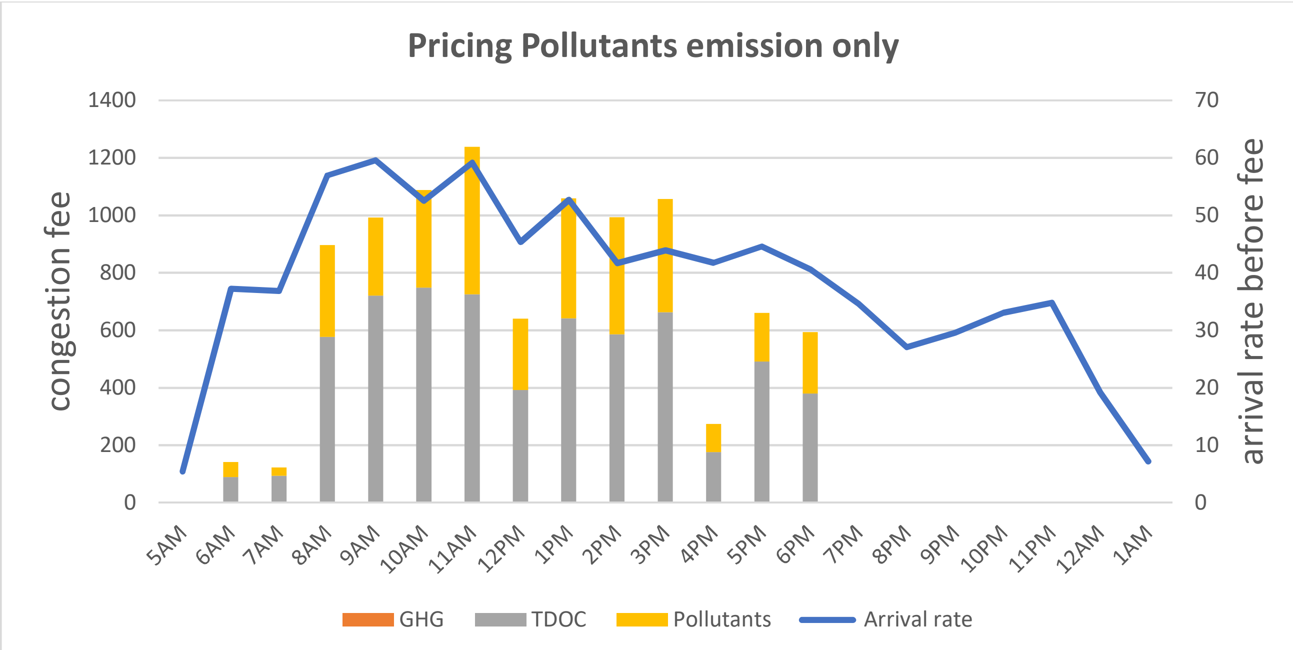


Figure 24. Congestion pricing with pollutants only

In scenario 2, I applied a congestion fee which price both pollutants and GHG emissions with the country-level social cost of carbon (CSCC). The results were shown in Figure 25. The maximum congestion fee is $1,266 at 11 am and the minimum fee is $125 at 7 am while the median fee is $675 at 8 am. Three components constitute the congestion fee with CSCC, the first part is due to the cost of the pollutants (marked with orange color), the second is due to the total direct operation cost (TDOC) (marked with grey color) and the third component is due to the GHG emission (marked with red color). GHG emission accounts for about 11% to 22% of total congestion fee, TDOC accounts for 31% to 33% of total congestion fee and pollutants account for 58% to 62% of total fee.

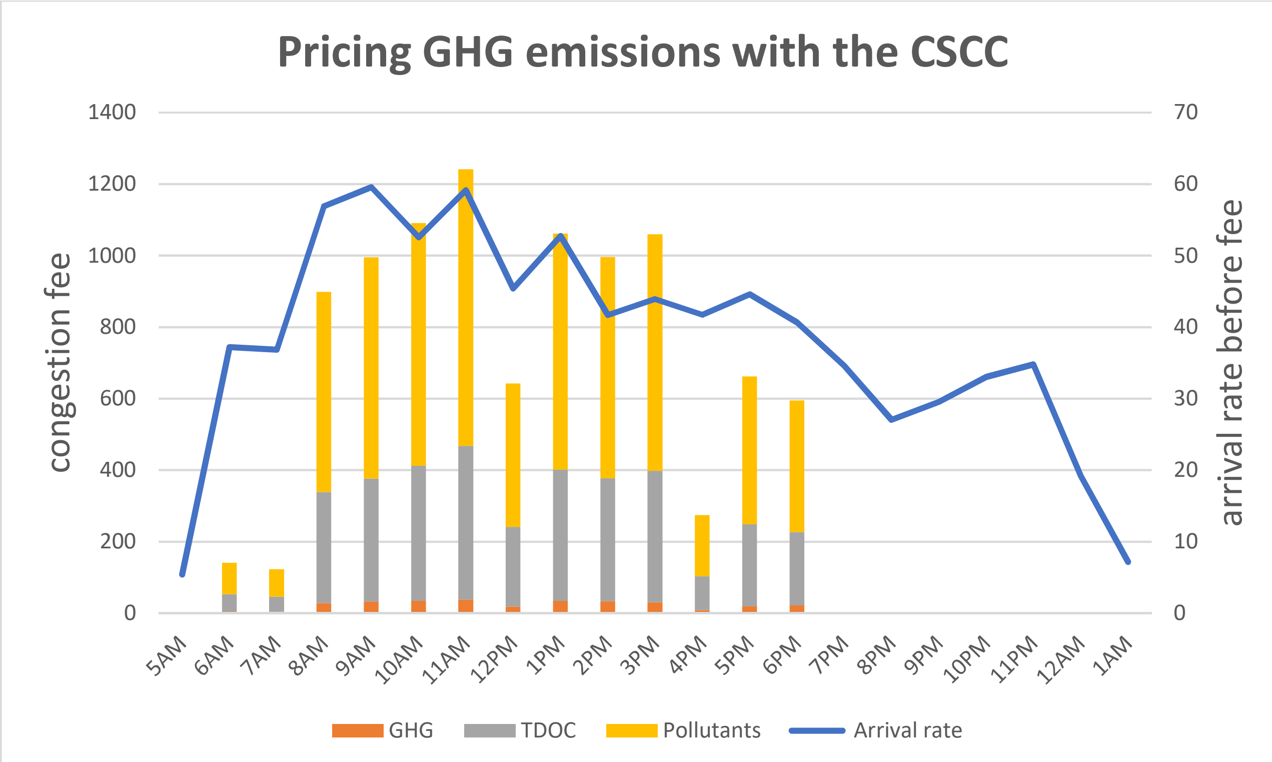


Figure 25. Congestion pricing with CSCC

In scenario 3, I applied a congestion fee which price both pollutants and GHG emissions with the global social cost of carbon (GSCC). In Figure 26, the maximum congestion fee is $1,560 at 11 am and the minimum fee is $154 at 7 am while the median fee is $1,129 at 8 am. Three components that constitute the congestion fee with GSCC, the first part is due to the cost of the pollutants which accounts for about 56% to 61% of total fee; the second component is due to the total direct operation cost (TDOC) which accounts for 29% to 34% of total congestion fee; and the third component is due to the GHG emission. GHG emission accounts for about 27% to 36% of total congestion fee.

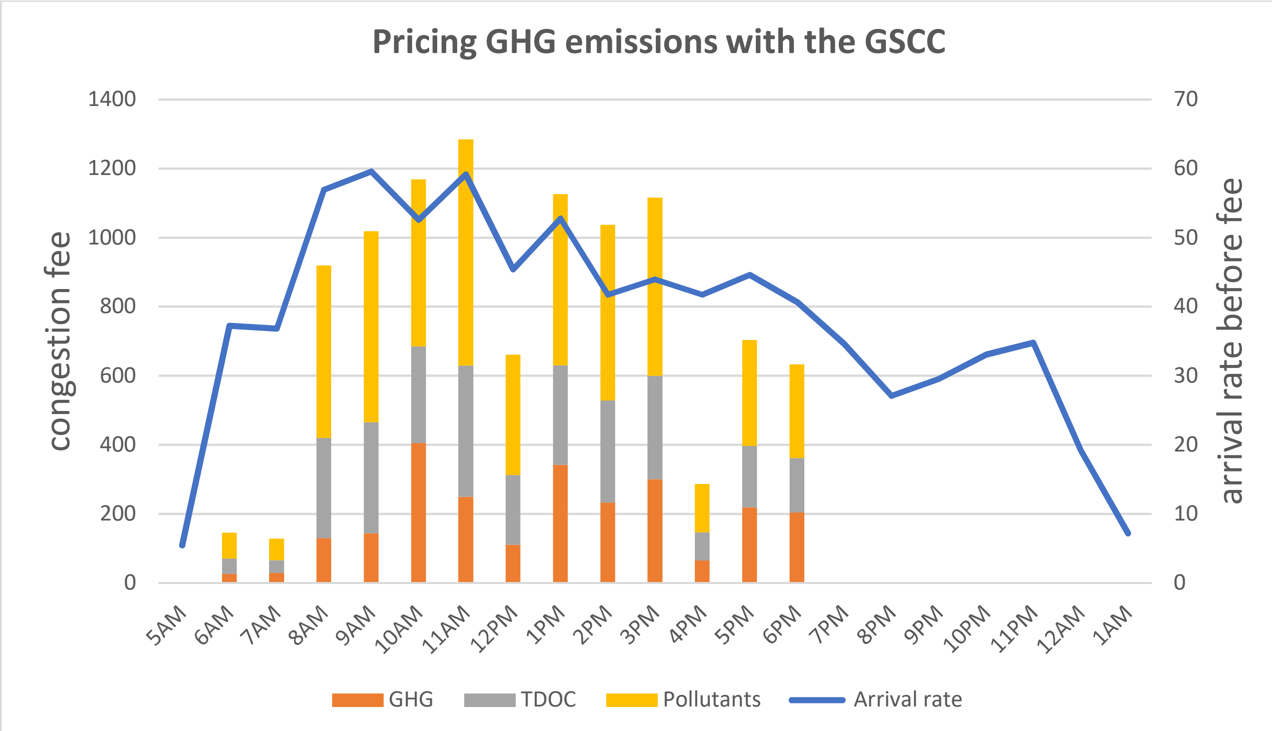


Figure 26. Congestion pricing with GSCC

6.2.2 Air quality changes

After obtaining the average annual mean of hourly $PM_{2.5}$ emissions for year 2014 from AEDT, I summarize the average annual mean for peak and off-peak seasons in Table 10. A congestion fee with CSCC may improve air quality over a year.

Table 10. Air quality concentrations from aviation after AERMOD dispersion

Average mean of all grid cells ($PM_{2.5}$ $\mu g/m^3$)	Before the congestion fee	After congestion fee (with CSCC)	Percentage change
Peak season	3.1	2.6	-16%
Off-peak season	2.4	2.1	-12%

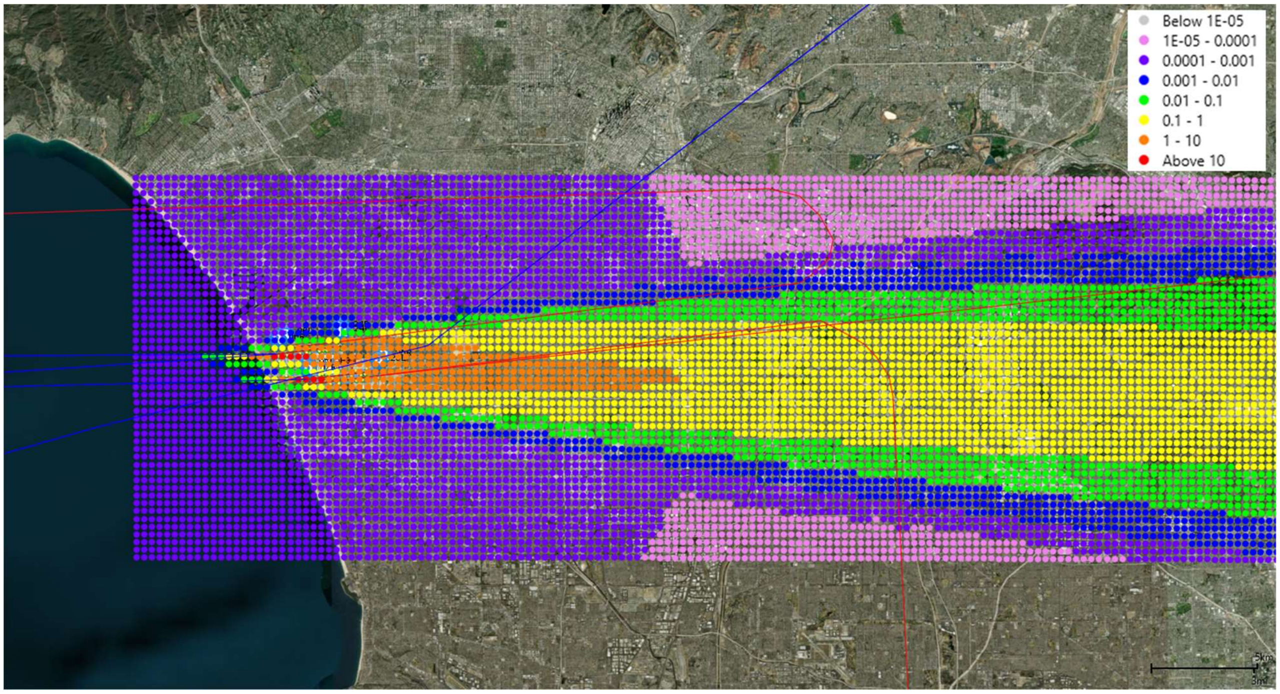


Figure 27. Dispersion of $PM_{2.5}$ ($\mu g/m^3$) after congestion fee

(with cost of pollutants only)

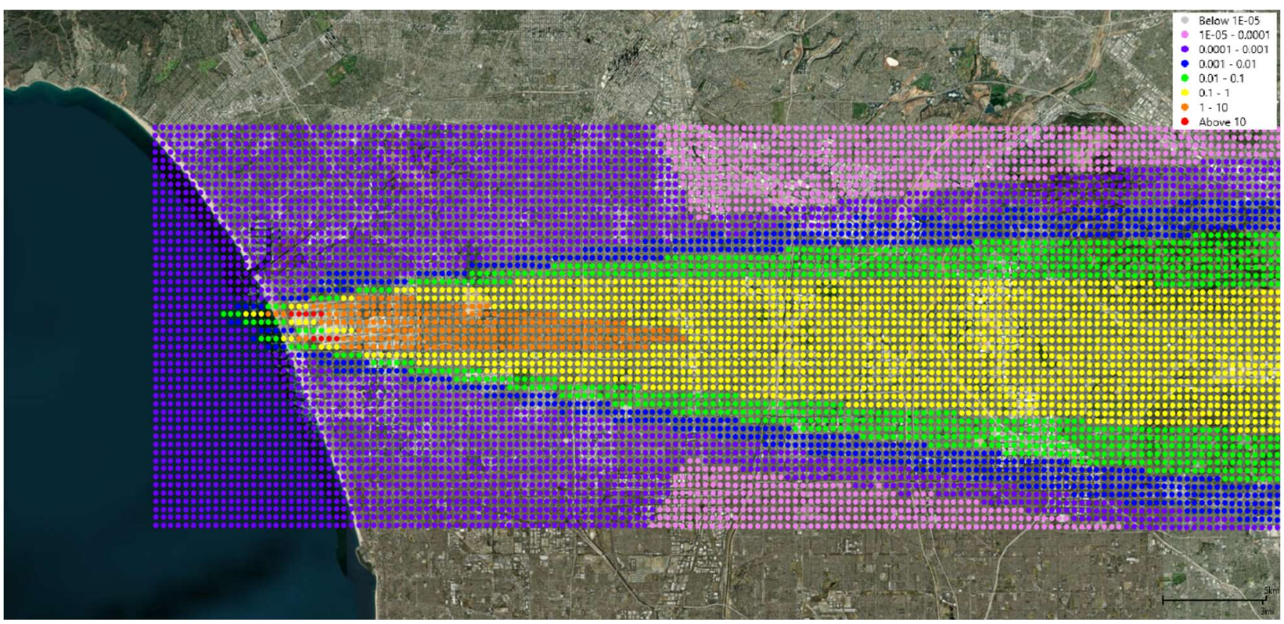


Figure 28. Dispersion of $PM_{2.5}$ ($\mu g/m^3$) after congestion fee

(with cost of pollutants and CSCC)

A congestion fee with CSCC may reduce average mean $PM_{2.5}$ by 16% in peak season and improve Off-peak season $PM_{2.5}$ by 12%. In addition, Table 11 shows that a congestion fee with GSCC helps further reduce aircraft congestion and $PM_{2.5}$ with a 29% improvement in peak season and 25% improvement in off-peak seasons. Figure 27 and 28 show the difference between scenario 1 and 2.

Table 11. Air quality concentrations from aviation after AERMOD dispersion

Average mean of all grid cells ($PM_{2.5}$ μg/m^3)	Before the congestion fee	After congestion fee (with GSCC)	Percentage change
Peak season	3.1	2.2	-29%
Off-peak season	2.4	1.8	-25%

6.2.3 Human health and climate benefits valuation

The BenMAP model was used to estimate resulting health benefits associated with exposures to the change in $PM_{2.5}$ concentrations attributable to the three different airport congestion fees. The BenMAP model is widely used to quantify and monetize potential health impacts associated with changes in air quality and contains concentration-response (C-R) functions for various pollutants including PM2.5. C-R functions are based on published studies incorporating different assumptions regarding potential thresholds and observed slopes between concentrations and responses.

Existing studies agree on the significant gap between domestic and global values of the SCC (Ricke, 2018). The GSCC is the sum of the CSCC values. For this study, I apply \$ \$417 per tonne for global social cost of carbon (GSCC) and EPA's estimation of $36 per tonne for the country-level social cost of carbon (CSCC). The one order magnitude (11.6 factors) is large enough to make a difference between the two scenarios in terms of congestion fee, air quality improvement, climate and health benefits.

Monetized estimates of premature mortality are based on estimates of the value of mortality risk as defined by the U.S. EPA (2018). BenMAP uses concentration–response (CR) functions to calculate the relationship between pollution and certain health effects, applying the relationship to the exposed population.

Implementing Scenario 2 and the results are showed in Table 12. The imposition of an airport congestion fee considering both pollutants and CSCC cost would reduce (1) premature mortality from $PM_{2.5}$ exposure by 4.9 cases (95 % CI: 2.2, 8) each year which have estimated monetary value 48.8 million (95% CI: 21.9, 79.7). (2) avoided hospital admissions for cardiovascular diseases by 175 cases (95 % CI: 82, 367) with estimated monetary value 23.6 million (95 % CI: 10.3, 45.9). (3) avoided hospital admissions for respiratory by 90 cases (95 % CI: 34, 146) with estimated monetary value 7.8 million (95 % CI: 3, 12.7) and (4) avoided work loss days by 9,017 units (95 % CI: 3,708, 13,998) with 1.5 million (95 % CI: 0.6, 2.3) monetary value (all in 2014 dollars).

Table 12. Economic valuation of health benefits from airport congestion fee.

	Disease incidence (# reduction/year)	Health benefits (million US $2014/year)
Premature mortality, all causes	4.9	48.8
	(95 % CI: 2.2, 8)	(95% CI: 21.9, 79.7)
Hospital admissions,	175	23.6
cardiovascular	(95 % CI: 82, 367)	(95 % CI: 10.3, 45.9)
Hospital admissions, respiratory	90	7.8
	(95 % CI:34, 146)	(95 % CI: 3, 12.7)
Impacted Days, work loss days	9,017	1.5
	(95 % CI: 3,708, 13,998)	(95 % CI: 0.6, 2.3)

Notes. CI = confidence interval. These results use the global social cost of carbon.

Table 13. Economic valuation of health benefits from airport congestion fee.

	Disease incidence (# reduction/year)	Health benefits (million US $2014/year)
Premature mortality, all causes	6	60.7
	(95 % CI: 2.1, 9)	(95% CI: 20.9, 89.6)
Hospital admissions,	221	27.7
cardiovascular	(95 % CI: 92, 350)	(95 % CI: 11.5, 43.8)
Hospital admissions, respiratory	114	9.9
	(95 % CI: 49, 179)	(95 % CI: 4.3, 15.6)
Impacted Days, work loss days	11,528	1.9
	(95 % CI: 4,995, 18,060)	(95 % CI: 0.8, 2.9)

Notes. CI = confidence interval. These results use the global social cost of carbon.

Table 14 and Table 15 provide a summary of predicted premature mortality, hospital admission and work loss days and associated monetized estimates of cost based on three different scenarios and on all 6 concentration-response functions. Predicted avoided premature mortalities range from 4.6 to 6 cases, depending on which environmental cost is used, which corresponds with approximately \$45.8M to \$60.7M in total monetary costs. The 2.5th and 97.5th percentiles (95 % confidence interval) from each scenario are included in the parentheses and represent the effect of uncertainty in the concentration-response functions in BenMap. Likewise, predicted avoided hospital admissions for cardiovascular range from 167 to 221 cases with corresponding \$21.9M to \$27.7M in avoided total monetary costs. Predicted avoided hospital admissions for respiratory range from 86 to 114 cases with corresponding \$7.5M to \$9.9M in avoided total monetary costs.

Predicted avoided work loss days range from 8,539 to 11,528 units with corresponding \$1.4M to \$1.9M in avoided total monetary costs.

Table 14. Health outcomes of congestion fees in different scenarios

	Scenario 1: Pricing pollutants only	**Scenario 2: Pricing GHG emissions with the CSCC**	**Scenario 3: Pricing GHG emissions with the GSCC**
Health endpoint	**Disease incidence (reduction/year)**	**Disease incidence (reduction/year)**	**Disease incidence (reduction/year)**
Premature mortality, All causes	4.6 (95 % CI: 3.1, 6)	4.9 (95 % CI: 2.2, 8)	6 (95 % CI: 2.1, 9)
Hospital admissions, Cardiovascular	167 (95 % CI: 71, 327)	175 (95 % CI: 82, 367)	221 (95 % CI: 92, 350)
Hospital admissions, Respiratory	86 (95 % CI:33, 140)	90 (95 % CI:34, 146)	114 (95 % CI:49, 179)
Impacted Days, Work loss days	8,539 (95 % CI: 3,511, 13,247)	9,017 (95 % CI: 3,708, 13,998)	11,528 (95 % CI: 4,995, 18,060)

Note: Country-level social cost of carbon (CSCC); Global social cost of carbon (GSCC).

Transitioning from the congestion fee with pollutants to congestion fee with both pollutants and CSCC will further prevent an estimated 0.3 premature deaths cases, 8 cases of hospital admissions for cardiovascular, 4 cases of hospital admissions for respiratory and 478 units of work loss days per year. In comparison, transitioning from the congestion fee with pollutants to the congestion fee with both pollutants and GSCC will further prevent an estimated 1.4 premature deaths cases, 54 cases of hospital admissions for cardiovascular, 28 cases of hospital admissions for respiratory and 2,989 units of work loss days per year.

Table 15. Health benefits of congestion fees in different scenarios

	Scenario 1: Pricing pollutants only	**Scenario 2: Pricing GHG emissions with the CSCC**	**Scenario 3: Pricing GHG emissions with the GSCC**
Health endpoint	**Health benefits (million U.S. 2014 $/yr)**	**Health benefits (million U.S. 2014 $/yr)**	**Health benefits (million U.S. 2014 $/yr)**
Premature mortality, All causes	45.8 (95% CI: 30.8, 59.7)	48.8 (95% CI: 21.9, 79.7)	60.7 (95% CI: 20.9, 89.6)
Hospital admissions, Cardiovascular	21.9 (95 % CI: 9.3, 42.8)	23.6 (95 % CI: 10.3, 45.9)	27.7 (95 % CI: 11.5, 43.8)
Hospital admissions, Respiratory	7.5 (95 % CI: 2.9, 12.2)	7.8 (95 % CI: 3, 12.7)	9.9 (95 % CI: 4.3, 15.6)
Impacted Days, Work loss days	1.4 (95 % CI: 0.6, 2.1)	1.5 (95 % CI: 0.6, 2.3)	1.9 (95 % CI: 0.8, 2.9)

Note: Country-level social cost of carbon (CSCC); Global social cost of carbon (GSCC).

Table 16. Airport health impacts

	Airport disease incidence (# case/year)
Premature mortality, all causes	18.2
	(95% CI: 6.9, 29.7)
Hospital admissions, cardiovascular	678
	(95 % CI: 104, 1,295)
Hospital admissions, respiratory	344
	(95 % CI: 62, 738)
	34,156
Impacted Days, work loss days	(95 % CI: 8,720, 59,031)

Although premature mortality drives the value of health losses (they are about 2 times larger than the value of hospital admissions for respiratory), it is important to note that the number of hospital admissions is 36 to 38 times greater than the number of premature mortalities.

The airport traffic of peak and off-peak seasons, after imposing a congestion fee, shows that all the congestion fee in three different scenarios are effective for improving air quality and health impacts. The global SCC (GSCC) captures the externality of CO_2 emissions and is thus the right value to use from a global welfare perspective. However, country-level contributions to the SCC are important as well because GSCC is the summation of CSGG for all countries considered.

Table 16 shows the health impacts of LAX, a congestion fee with pollutants may reduce premature mortality by 25 %, from 18.2 cases to 13.6 cases. A congestion fee with both pollutants and CSCC will reduce premature mortality by 27% from 18.2 cases to 13.3 cases, while a congestion fee with both pollutants and GSCC will further reduce premature mortality by 33% from 18.2 cases to 12.2 cases. Compared the improvement of health impacts with the improvement of air quality concentrations from aviation, the health benefits of airport congestion fees are larger than the air quality improvement (Table 11). Such results correspond to recent researches for the C-R function.

A Concentration-Response (C-R) function estimates the relationship between adverse health effects and ambient air pollution. Although current evidence suggests that the C-R function between $PM_{2.5}$ air pollution and mortality risk is approximately linear for a relatively narrow range at low levels of pollution (Pope *et al.*, 2002), recent research suggests that the C-R function is likely to be concave for wide ranges that include higher levels of exposure (Pope *et al.*, 2009; Burnett *et al.*, 2014). Such results appear to imply that a given reduction in concentrations will yield greater benefits in relatively clean areas than in highly polluted areas (Goodkind *et al.*, 2014).

A summary of airport traffic, time saved and fuel saved from the airport congestion fee is presented in Table 17. The number of aircraft arrival is 296,482 and the number of aircraft departure is 297,065, both arrivals and departures are with an average 135 number of seats in 2014. In peak season, average time saved for arrivals and departures are 2.2 and 2.9 minutes respectively since taxi-out time is usually longer than taxi-in time and hence the improvement of delay is larger for departure. Accordingly, total time saved for all arrival and departure aircraft is 3,100 hours and 4,052 hours in peak season and total time saved for all arrival and departure 5,926 hours and 8,305 hours in 2014. The fuel saved for all arrival and departure aircraft can be as large as 12,714 tons and 17,819 tons yearly, which are corresponding to CO_2 emission of 40,176 and 56,308 tons respectively with the jet fuel to CO_2 ratio of 3.16 recommended by ICAO (2014).

Table 17. Airport traffic, saved taxi time, fuel saved

	Peak season (3 months)	**Off-peak seasons (9 months)**	**The year 2014 (12 months)**
# of aircraft arrival	84,540	211,942	296,482
Average number of seats per arrival	138	134	135
# of aircraft departure	84,415	212,650	297,065
Average number of seats per departure	138	134	135
Average time saved for arrivals	2.2	0.8	1.2
Average time saved for departures	2.9	1.2	1.7
Total time saved for all arrival aircraft (hour)	3,100	2,826	5,926
Total time saved for all departures aircraft (hour)	4,052	4,253	8,305
Maximal fuel saved (ton) for all arrivals	6,651	6,063	12,714
Minimal fuel saved (ton) for all arrivals	5,741	5,234	10,975
Maximal fuel saved for all departures	8,694	9,125	17,819
Minimal fuel saved for all departures	7,504	7,877	15,381
CO_2 emission (ton)	- 48,490	- 47,994	- 96,486

Notes.
1. Waiting time saved in airways and taxiways (unit: minute).
2. Average fuel consumption is 35.76 kg per minute. It is calculated from multiplying fuel-burn rate for LTO cycle in Table 5 weighted by Aircraft portfolio of LAX in Figure 10.
Source: Traffic Flow Management System Counts (TFMSC) & compiled by the author.

Chapter 7 Conclusions

This is the first study to quantify and monetize the number of avoided deaths associated with a reduction in $PM_{2.5}$ concentrations from an airport congestion pricing scheme. This dissertation analyzes congestion and emissions based on the fact that more congestion produces more emissions in airports. The congestion fee is intended to correct over-capacity airport traffic and does so by setting the congestion fee equal to the economically and environmentally social cost of the negative externalities, including delay cost and emission cost from jet engines, APU and GSEs.

For study inclusion, I prioritized most recent updates of multicity studies, large prospective cohort studies and studies assessing health impacts across wide age ranges. The analysis shows that when an airport imposes a proper Pigovian tax, a fee that captures the uninternalized portion of the economic, environmental and health cost of congestion, it improves the allocation of traffic and spread out the traffic throughout the operation hours. The analysis is supported by our simulation using empirical data from Los Angeles International Airport. I apply discrete-event simulation (DES) to simulate the aircraft's movements because DES is a computer modeling tool that can replicate complex systems. The emission inventory uses FAA's AEDT and detailed activity data for aircraft main engines, auxiliary power unit (APU) and aircraft ground support equipment (GSEs) equipment together with the time-in-modes and location of their use at LAX. EPA's BenMAP uses baseline air quality, control air quality and valuation functions to estimate the monetized benefits of reducing air pollution.

There are several caveats to consider when interpreting the results of this analysis. First, health impacts are estimated only in areas that population data is available from the SEDAC.

SEDAC data does not include passengers and workers in the airport who may have longer exposure time and a larger magnitude. Without a valid population count for passengers and staff, I was unable to accurately estimate the potential impacts of air quality in these groups. However, these people likely will benefit more since they are closer to the emission sources and thus will experience more reduction in exposure. Second, automobiles taking travelers to and from the airport is another important source of emission.

As oppose to a primary pollutant which is an air pollutant emitted directly from a source, A secondary pollutant is not directly emitted as such, but forms when other pollutants (primary pollutants) react in the atmosphere. This increase the complexity of estimating the secondary pollutants from aviation activities because emissions from other sources (mobiles and maritime) have to be taken into account. For example, Ozone is formed throughout the atmosphere in multistep chemical processes that require sunlight, the time and amount of a secondary pollutant varies.

I simulated the dispersion of primary PM emissions from airport operations and did not consider the chemical transformation of PM into secondary pollutants. To also estimate the health impacts related to secondary PM, all related pollutant background concentrations involved in the chemical transformation reactions, as well as the primary emissions and the chemical transformation of these related pollutants, would need to be modeled. Therefore, the AERMOD simulations did not consider chemical transformation, and the air quality and health impacts of species such as secondary particulate matter, ozone and hydrogen peroxide are left to future work.

It is worth to note that the range of expected health benefits I report is conservative because I did not account for secondary PM. Although its impact may be substantial (Behera and Sharma, 2010).

Future studies may collect the number of passengers and staff of airports and extend the estimation of the benefits for these people. I recommend using EPA's Motor Vehicle Emission Simulator (MOVES) emission modeling system to estimates emissions for mobile sources of roadways, parking facilities at airports. MOVES must be used to generate emissions inventories as AERMOD input files for on-road or off-road mobile sources. Lastly, the purpose of our analysis is not to demonstrate causation between exposure to $PM_{2.5}$ air pollution and adverse health effects. Our estimates of saved mortality, hospital admission and impact days are based on observed associations between exposure to $PM_{2.5}$ and adverse health outcomes from epidemiology studies.

However, the results presented in this study can help assess how airport demand management measures (e.g. congestion pricing, time slot allocation) could reduce attributable mortality, hospital admissions and impacted days from $PM_{2.5}$ and it can be expanded to regional and country scale and provides useful insight to policymakers in identifying potential environmental benefits of reducing airport congestion. Other future studies could expand the concept to the cost-benefit analyses of airport supply management (e.g. new airport or runway construction) and demand management.

Appendix A. Simulation results from DES (SIMMER)

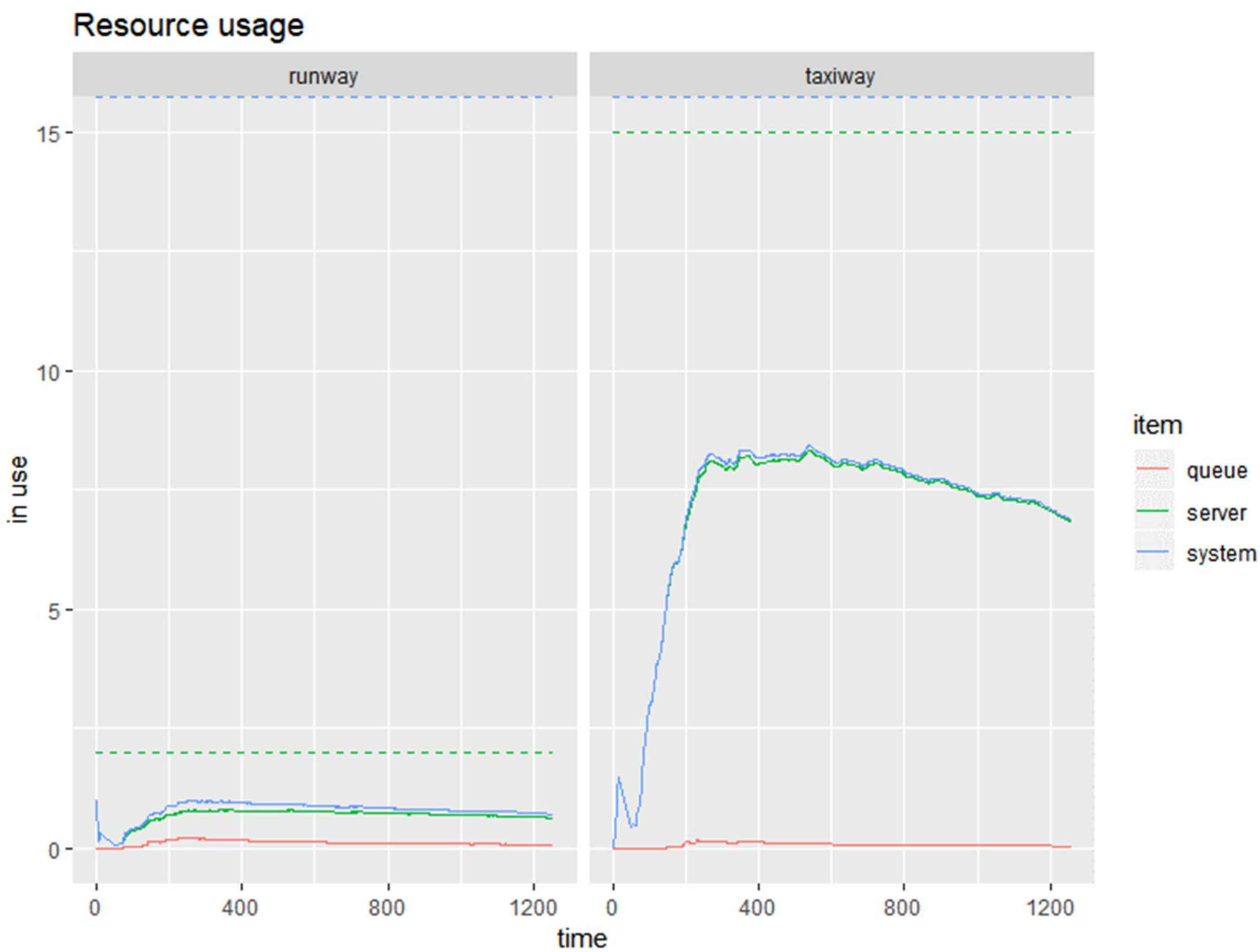


Figure 29. Usage of runways and taxiway before congestion fee

(Source: DES; Unit: minute and number of aircraft)

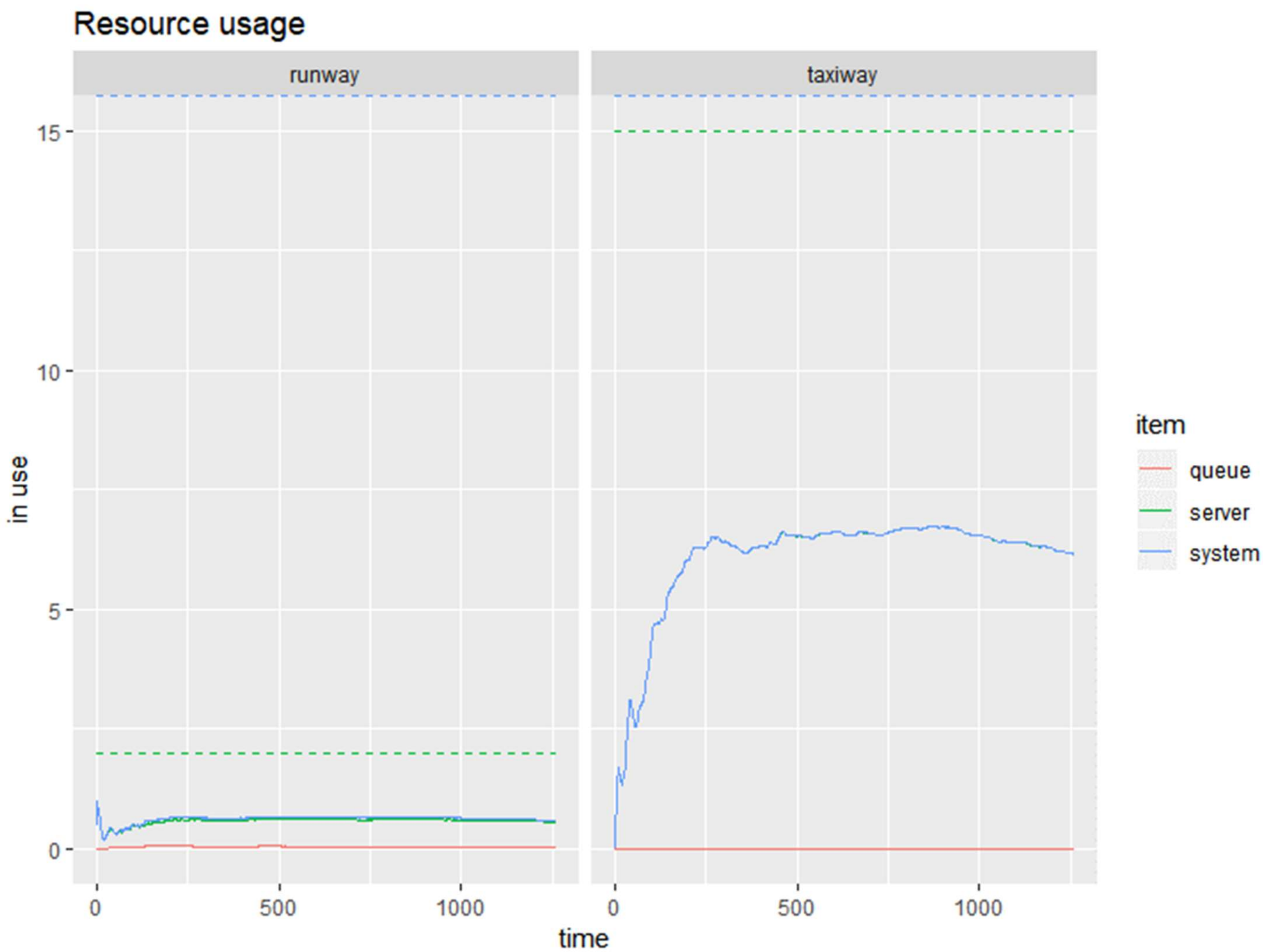


Figure 30. Usage of runways and taxiway after congestion fee

(Source: DES; Unit: minute and number of aircraft)

Note:

1. **Redline**: number of aircraft in a queue.

2. **Greenline**: number of runway or taxiway.

3. **Blueline**: number of aircraft in the system (number of aircraft in a queue and in-service).

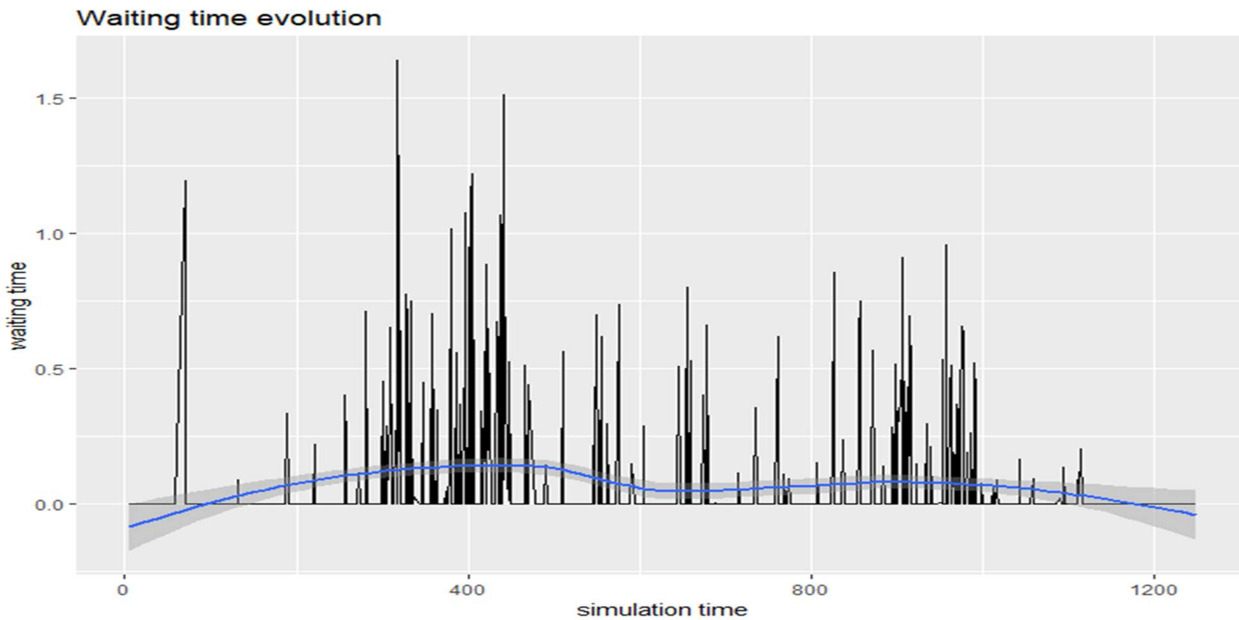


Figure 31. Waiting time for a runway in off-peak seasons

(before congestion fee)

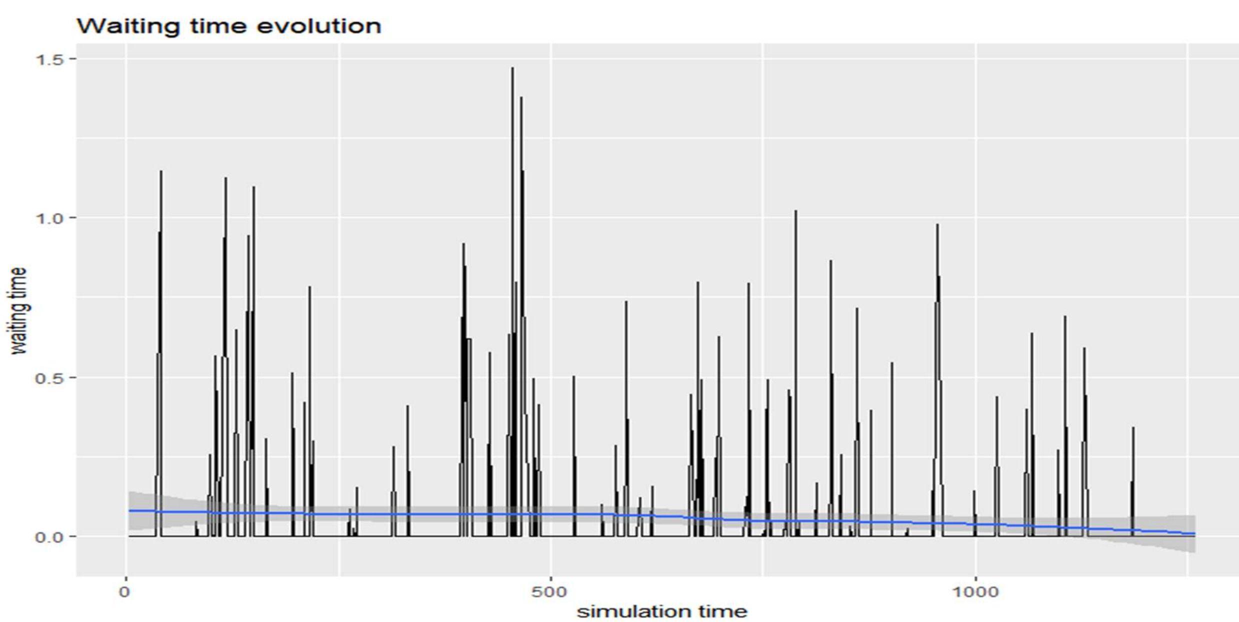


Figure 32. Waiting time for a runway in off-peak seasons

(after congestion fee)

Appendix B. The transition of queue

I first start with a landing queue where in LAX's Westerly Operations in normal daytime, there are two outer runways are designated to only landing, the number of servers for landing queue is 2 (S=2). The number of arrivals in each hour is assumed to be a Poisson-distributed with arrival rate of λ_t flights per hour. $q_{t+1} = Q_t q_t$

A state vector, q_t, represents the state of the queuing system at each time *t* and it give the probability that the queue is of length 0, 1, 2, ... , K at the beginning of time *t*. For example, the state of the queuing at time *t* is a *K+1* by *1* vector, $\left[q_t^0 \; q_t^1 \; \cdots \; q_t^{K-1} \; q_t^K\right]^T$. The subscript *t* means the current time and superscript numbers mean the number aircraft in the queue. The state vector q_t evolves according to the transition rule $q_{t+1} = Q_t q_t$ where q_{t+1} is the state vector at time *t+1*, it depends on the previous state vector q_t and the state-transition matrix Q_t with arrival rates λ_t. Each element of the state-transition matrix Q_t in the i^{th} row and j^{th} column, Q_{ij}, is the probability that the transition from being *j-1* aircraft in the queue at the beginning of the current time *t* to being *i-1* aircraft in the queue at the beginning of the next time slot *t+1*.

Transition Rule for Arrival (and Departure) Queue

Detail of the transition rule $\boldsymbol{q_{t+1}} = \boldsymbol{Q_t}\,\boldsymbol{q_t}$:

$$
\begin{bmatrix}
\sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \frac{(\lambda_t)^0 e^{-\lambda_t}}{0!} & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\
\sum_{i=0}^{3}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \frac{(\lambda_t)^0 e^{-\lambda_t}}{0!} & 0 & & 0 & 0 & \cdots & 0 \\
\sum_{i=0}^{4}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{3}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \frac{(\lambda_t)^0 e^{-\lambda_t}}{0!} & & 0 & 0 & \cdots & 0 \\
. & & \cdots & & & & 0 & 0 & \cdots & 0 \\
. & . & & . & . & . & & & & \\
. & . & \cdots & . & . & . & & & & \\
\sum_{i=0}^{K+1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{K}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & & \cdots & \cdots & & \sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & & & \sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} \\
\sum_{i=0}^{K+2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & \sum_{i=0}^{K+1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & & \cdots & \cdots & & \sum_{i=0}^{3}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!} & & & \sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!}
\end{bmatrix}
\begin{bmatrix} q_t^0 \\ q_t^1 \\ q_t^2 \\ q_t^3 \\ . \\ . \\ . \\ . \\ . \\ . \\ q_t^{K-1} \\ q_t^K \end{bmatrix}
=
\begin{bmatrix} q_{t+1}^0 \\ q_{t+1}^1 \\ q_{t+1}^2 \\ q_{t+1}^3 \\ . \\ . \\ . \\ . \\ . \\ q_{t+1}^{K-1} \\ q_{t+1}^K \end{bmatrix}
$$

where $\boldsymbol{Q_t}$ is a *(K+1)* by *(K+1)* matrix

$\boldsymbol{q_t}$ is a *(K+1)* by *1* vector

$\boldsymbol{q_{t+1}}$ is a *(K+1)* by *1* vector

Detail of derivative of $\boldsymbol{q_{t+1}}$, $\boldsymbol{D_t}$

$$
e^{-\lambda_t}\cdot
\begin{bmatrix}
\sum_{i=0}^{2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \frac{(\lambda_t)^0}{0!} & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\
\sum_{i=0}^{3}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \frac{(\lambda_t)^0}{0!} & 0 & 0 & 0 & \cdots & & 0 \\
\sum_{i=0}^{4}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{3}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \frac{(\lambda_t)^0}{0!} & 0 & 0 & \cdots & & 0 \\
. & \cdots & 0 \quad 0 & \cdots & 0 & \cdots & & & & \\
. & . & . & . & . & & & & & \\
. & . \quad \cdots & . & . & . & & & & & \\
\sum_{i=0}^{K+1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{K}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & & \cdots & \cdots & & & \sum_{i=0}^{2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & & \sum_{i=0}^{1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} \\
\sum_{i=0}^{K+2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & \sum_{i=0}^{K+1}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & & \cdots & \cdots & & & \sum_{i=0}^{3}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!} & & \sum_{i=0}^{2}\frac{i(\lambda_t)^{i-1}+(\lambda_t)^i}{i!}
\end{bmatrix}
$$

Since LAX have 2 runways for serving incoming flights and the other two serves outgoing flight. Take arrival aircraft queue for example, there are at most 2 aircraft can land on the outer runways. Likewise, for departure aircraft queue, only 2 aircraft can takeoff at the same time. K is the capacity of queue, any number of aircraft ranges from 0 to K in the is possible of a queue. In other words, K is the maximum aircraft that a queue (airway or taxiway buffer) can hold. The first entry of q_{t+1}, q_{t+1}^0 is the probability that in the beginning of time *t+1*, the queue length is 0 or no queue. The probability of being no queue in the beginning of *t+1* equal to the sum of the probabilities of (1) when both runways are available at time t (probability: q_t^0) and only 0,1 or 2 aircraft land (probability: $\sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!}$) in time *t*. (2) when only one runway is available (probability: q_t^1) and only 0 or 1 aircraft land (probability: $\sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!}$) (3) when both runways are occupied (probability: q_t^2) and no aircraft show off to land (probability: $\frac{(\lambda_t)^0 e^{-\lambda_t}}{0!}$).

$$
\begin{aligned}
\mathrm{q}_{t+1}^0 = &\left[\sum_{i=0}^{2}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!}\right] q_t^0 && (1)\\
&+\left[\sum_{i=0}^{1}\frac{(\lambda_t)^i e^{-\lambda_t}}{i!}\right] q_t^1 && (2)\\
&+\left[\frac{(\lambda_t)^0 e^{-\lambda_t}}{0!}\right] q_t^2 && (3)\\
&+0q_t^3\\
&.\\
&.\\
&.\\
&+0q_t^K
\end{aligned}
$$

or

$$
\begin{aligned}
\mathrm{q}_{t+1}^0 = &e^{\lambda_t} q_t^0 + (\lambda_t e^{-\lambda_t}) q_t^0 + (\frac{(\lambda_t)^2 e^{-\lambda_t}}{2!}) q_t^0 && (1)\\
&+e^{\lambda_t} q_t^1 + (\lambda_t e^{-\lambda_t}) q_t^1 && (2)\\
&+e^{\lambda_t} q_t^2 && (3)\\
&+0q_t^3\\
&.\\
&.\\
&.\\
&+0q_t^K
\end{aligned}
$$

Appendix C. R code for discrete-event simulation (DES)

```
## import libraries

library(simmer)
library(parallel)
library(simmer.plot)
library(simmer.bricks)

set.seed(12345)

## set trajectory for DES

LAX <- simmer()

TRAJ_arrival <- trajectory("arrival") %>%

  set_attribute("start_time", function() {now(LAX)}) %>%

 ## add a runway activity, seize a runway resource
 ## Reference for runway, taxiways and gate time
 ## Los Angeles world airports, www.lawa.org

 seize("runway", 1) %>%
 timeout(function() rnorm(1, 0.9, 0.1)) %>%
 release("runway", 1) %>%



 ## add a taxiway activity
```

```
seize("taxiway", 1) %>%
timeout(function() rnorm(1, 10.1, 3)) %>%
release("taxiway", 1) %>%

##add a gate activity

  seize("gate", 1) %>%
  timeout(function() rnorm(1,43, 15)) %>%
  release("gate", 1)


log_(function() {paste("Waited in queues: ", now(LAX) - get_attribute(LAX, "start_time"))})


## set arrival rate lamda (flights per minute)
## changeable, depending on which month I study

lamda_05    <-    0.184408602
lamda_06    <-    0.540860215
lamda_07    <-    0.514516129
lamda_08    <-    0.877956989
lamda_09    <-    0.78655914
lamda_10    <-    0.693010753
lamda_11    <-    0.848387097
lamda_12    <-    0.814516129
lamda_13    <-    0.925806452
lamda_14    <-    0.588172043
lamda_15    <-    0.591935484
```

```
lamda_16    <-    0.746774194
lamda_17    <-    0.654301075
lamda_18    <-    0.647849462
lamda_19    <-    0.688172043
lamda_20    <-    0.80483871
lamda_21    <-    0.577956989
lamda_22    <-    0.511827957
lamda_23    <-    0.368817204
lamda_24    <-    0.448924731
lamda_01    <-    0.437096774


## define  function of airplane arrival rate

rate_05 <- function() rexp(1, lamda_05)
rate_06 <- function() rexp(1, lamda_06)
rate_07 <- function() rexp(1, lamda_07)
rate_08 <- function() rexp(1, lamda_08)
rate_09 <- function() rexp(1, lamda_09)
rate_10 <- function() rexp(1, lamda_10)
rate_11 <- function() rexp(1, lamda_11)
rate_12 <- function() rexp(1, lamda_12)
rate_13 <- function() rexp(1, lamda_13)
rate_14 <- function() rexp(1, lamda_14)
rate_15 <- function() rexp(1, lamda_15)
rate_16 <- function() rexp(1, lamda_16)
rate_17 <- function() rexp(1, lamda_17)
rate_18 <- function() rexp(1, lamda_18)
rate_19 <- function() rexp(1, lamda_19)
```

```
rate_20 <- function() rexp(1, lamda_20)
rate_21 <- function() rexp(1, lamda_21)
rate_22 <- function() rexp(1, lamda_22)
rate_23 <- function() rexp(1, lamda_23)
rate_24 <- function() rexp(1, lamda_24)
rate_01 <- function() rexp(1, lamda_01)

## set resources and add aircraft generator
LAX <- simmer("LAX") %>%

 add_resource("runway", 2) %>%          ## 2 inner runways for departure,
                                        ## the other 2 outer runways for arrival
 add_resource("taxiway", 17) %>%        ## evenly distribute aircraft to taxiways
 add_resource("gate", 132) %>%          ## evenly distribute aircraft to gates

 add_generator("05_Approach", TRAJ_arrival, from_to(  0,  60, rate_05)) %>%
 add_generator("06_Approach", TRAJ_arrival, from_to( 60, 120, rate_06))%>%
 add_generator("07_Approach", TRAJ_arrival, from_to(120, 180, rate_07))%>%
 add_generator("08_Approach", TRAJ_arrival, from_to(180, 240, rate_08))%>%
 add_generator("09_Approach", TRAJ_arrival, from_to(240, 300, rate_09))%>%
 add_generator("10_Approach", TRAJ_arrival, from_to(300, 360, rate_10))%>%
 add_generator("11_Approach", TRAJ_arrival, from_to(360, 420, rate_11))%>%
 add_generator("12_Approach", TRAJ_arrival, from_to(420, 480, rate_12))%>%
 add_generator("13_Approach", TRAJ_arrival, from_to(480, 540, rate_13))%>%
 add_generator("14_Approach", TRAJ_arrival, from_to(540, 600, rate_14))%>%
 add_generator("15_Approach", TRAJ_arrival, from_to(600, 660, rate_15))%>%
 add_generator("16_Approach", TRAJ_arrival, from_to(660, 720, rate_16))%>%
 add_generator("17_Approach", TRAJ_arrival, from_to(720, 780, rate_17))%>%
 add_generator("18_Approach", TRAJ_arrival, from_to(780, 840, rate_18))%>%
```

```
  add_generator("19_Approach", TRAJ_arrival, from_to(840, 900, rate_19))%>%
  add_generator("20_Approach", TRAJ_arrival, from_to(900, 960, rate_20))%>%
  add_generator("21_Approach", TRAJ_arrival, from_to(960, 1020, rate_21))%>%
  add_generator("22_Approach", TRAJ_arrival, from_to(1020, 1080, rate_22))%>%
  add_generator("23_Approach", TRAJ_arrival, from_to(1080, 1140, rate_23))%>%
  add_generator("24_Approach", TRAJ_arrival, from_to(1140, 1200, rate_24))%>%
  add_generator("01_Approach", TRAJ_arrival, from_to(1200, 1260, rate_01))

options(max.print=999999)

## run for 21 hours = 1260 minutes

LAX %>% run(until = 1260)%>%
  get_mon_arrivals()
```

Appendix D. R code for airport congestion fee

```
##First order derivative of cots for arrival flights

##Total direct operating costs (TDOC) is $65.23 per minute in the 2014 term,

##2014 jet fuel price: 1.8/gallon=0.5921/kg

##The environmental cost of APU and jet engines (C_je_APU) derived from

##(Lu and Morrell, 2006; Kinsey et al., 2012; ICAO, 2019) and

##the unit environmental costs per pollutant given in Table 2 on page 42 of
dissertation (chapter 3.2.4).


## import library

library(Deriv)

# set costs

C_tdop <- 65.23

C_k <- 116.1757333

## number of flight in each time slot (January)

N <- c(6.032258065,

    32.09677419,
```

47.38709677,

67.12903226,

46.96774194,

47.58064516,

54.41935484,

49.67741935,

51.77419355,

44.77419355,

35.67741935,

41.87096774,

46.96774194,

32.22580645,

34.58064516,

29.32258065,

26.22580645,

37.64516129,

27.93548387,

18.29032258,

```
    4.580645161)

K <- 2

## average arrival time between two difference aircraft at time slot

lamda_t <- c(0.100537634,
        0.534946237,
        0.789784946,
        1.118817204,
        0.782795699,
        0.793010753,
        0.906989247,
        0.827956989,
        0.862903226,
        0.746236559,
        0.594623656,
        0.697849462,
        0.782795699,
        0.537096774,
        0.576344086,
```

```
          0.488709677,

          0.437096774,

          0.627419355,

          0.465591398,

          0.30483871,

          0.076344086)


l <- 2.6        ##average queue length

tau_A <- 1.9

delta_l <-  1.5    ##average number of difference between two queue


## difference between two arrival rates

delta_lamda <-  c(0.100537634,

             0.434408602,

             0.25483871,

             0.329032258,

             -0.336021505,

             0.010215054,
```

0.113978495,

-0.079032258,

0.034946237,

-0.116666667,

-0.151612903,

0.103225806,

0.084946237,

-0.245698925,

0.039247312,

-0.087634409,

-0.051612903,

0.190322581,

-0.161827957,

-0.160752688,

-0.228494624)

congestion fees

FOC_sum <- 0

```
for (t in 1:21)

{

  for (n in 1:N[t])

    for (k in 1:K)

    {

      FOC_cost = (C_tdop+C_je)*((k*lamda_t[t])^(k-1)-lamda_t[t]^(k-1))*exp(-
lamda_t[t])/factorial(k)*l+lamda_t[t]^k*exp(-
lamda_t[t])/factorial(k)*delta_l/delta_lamda[t]

      FOC_sum = FOC_sum + FOC_cost

      }

  print (FOC_sum)

    FOC_sum <- 0                    ## reset for next iteration and time slot

}
```

Appendix E. ICAO definition of landing and takeoff (LTO)

	% of thrust	**Duration (minute)**
Take-off	100	0.7
Climb	85	2.2
Approach	30	4
Taxi	7	26

Souce: International Civil Aviation Organization

References

Ahearn, M., Boeker, E., Gorshkov, S., Hansen, A., Hwang, S., Koopmann, J., ... & Solman, G. B. (2016). *Aviation Environmental Design Tool (AEDT) Technical Manual: Version 2c* (No. DOT-VNTSC-FAA-16-17). United States. Federal Aviation Administration. Office of Environment and Energy.

Airbus, S. A. S. (2004). Getting to grips with Fuel Economy. *Flight Operations Support & Line Assistance*, (4).

Anderson, K., & Bows, A. (2008). Reframing the climate change challenge in light of post-2000

Aravena, O., Basso, L. J., & Figueroa, N. (2019). Effects of asymmetric information on airport congestion management mechanisms. International Journal of Industrial Organization, 62, 4-27.

Arunachalam, S., Wang, B., Davis, N., Baek, B. H., & Levy, J. I. (2011). Effect of chemistry-transport model scale and resolution on population exposure to $PM_{2.5}$ from aircraft emissions during landing and takeoff. *Atmospheric Environment*, *45*(19), 3294-3300.

Ater, I. (2012). Internalization of congestion at US hub airports. *Journal of Urban Economics*, *72*(2-3), 196-209.

Babin, S. M., Burkom, H. S., Holtry, R. S., Tabernero, N. R., Stokes, L. D., Davies-Cole, J. O., ... & Lee, D. H. (2007). Pediatric patient asthma-related emergency department visits and admissions in Washington, DC, from 2001–2004, and associations with air quality, socio-economic status and age group. *Environmental Health*, *6*(1), 9.

Barbour, A. D., Holst, L., & Janson, S. (1992). *Poisson approximation* (Vol. 2). The Clarendon Press Oxford University Press.

Barrett, S. R., Britter, R. E., & Waitz, I. A. (2010). Global mortality attributable to aircraft cruise emissions. *Environmental science & technology*, *44*(19), 7736-7742.

Basso, L. J. and Zhang, A. (2010) 'Pricing vs. slot policies when airport profits matter', *Transportation Research Part B: Methodological*. doi: 10.1016/j.trb.2009.09.005.

Basso, L. J. and Zhang, A. (2010) 'Pricing vs. slot policies when airport profits matter', Transportation Research Part B: Methodological. doi: 10.1016/j.trb.2009.09.005.

Bauer, I., & Pannen, B. H. (2009). Bench-to-bedside review: carbon monoxide–from mitochondrial poisoning to therapeutic use. *Critical Care*, *13*(4), 220.

Baumgarten, P., Malina, R., & Lange, A. (2014). The impact of hubbing concentration on flight delays within airline networks: An empirical analysis of the US domestic market. *Transportation Research Part E: Logistics and Transportation Review*, *66*, 103-114.

Behera, S. N., & Sharma, M. (2010). Reconstructing primary and secondary components of PM2. 5 composition for an urban atmosphere. *Aerosol Science and Technology*, *44*(11), 983-992.

Bernardo, J. E., LeVine, M. J., Kirby, M. R., & Mavris, D. (2017). Analysis of aircraft vehicle class contributions to airport noise exposure. *Journal of Aerospace Operations*, *4*(4), 185-206.

Beychok, M. R. (2005). *Fundamentals of stack gas dispersion*. MR Beychok. ISBN 0-9644588-0-2. Windisch, J., Väätäinen, K., Anttila, P., Nivala, M., Laitila, J., Asikainen, A., & Sikanen, L. (2015). Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. *Applied energy*, *149*, 315-325.

Bows-Larkin, A., Mander, S. L., Traut, M. B., Anderson, K. L., & Wood, F. R. (2010). Aviation and climate change–the continuing challenge. *Encyclopedia of aerospace engineering*, 1-11.

Bracaglia, V., & Nastasi, A. (2014). Competition between multiproduct airports. *Economics of Transportation*, *3*(4), 270-281.

Brook, R. D., Rajagopalan, S., Pope III, C. A., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., ... & Peters, A. (2010). Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation*, *121*(21), 2331-2378.

Brueckner, J. K. (2002). Airport congestion when carriers have market power. *American Economic Review*, *92*(5), 1357-1375.

Brueckner, J. K. (2005). Internalization of airport congestion: A network analysis. *International Journal of Industrial Organization*, 23(7), 599-614.

Brueckner, J. K. (2009). Price vs. quantity-based approaches to airport congestion management. *Journal of Public Economics*, 93(5), 681-690.

Brueckner, J. K. (2009). Price vs. quantity-based approaches to airport congestion management. *Journal of Public Economics*, *93*(5-6), 681-690.

Brunekreef, B., & Holgate, S. T. (2002). Air pollution and health. *The lancet*, *360*(9341), 1233-1242.

Burnett, R. T., Pope III, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., ... & Anderson, H. R. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental health perspectives*, *122*(4), 397-403.

Burnett, R. T., Pope III, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., ... & Anderson, H. R. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental health perspectives*, *122*(4), 397-403.

Buxton, N. (2016). COP 21 charades: Spin, lies and real hope in paris. *Globalizations*, *13*(6), 934-937.

Carlin, A., & Park, R. E. (1970). Marginal cost pricing of airport runway capacity. The American Economic Review, 60(3), 310-319.

Carslaw, D. C., Beevers, S. D., Ropkins, K., & Bell, M. C. (2006). Detecting and quantifying aircraft and other on-airport contributions to ambient nitrogen oxides in the vicinity of a large international airport. *Atmospheric Environment*, *40*(28), 5424-5434.

Chen, L., Shi, M., Gao, S., Li, S., Mao, J., Zhang, H., ... & Wang, Z. (2017). Assessment of population exposure to $PM_{2.5}$ for mortality in China and its public health benefit based on BenMAP. *Environmental Pollution*, *221*, 311-317.

Cheng, Q., Liu, Z., Liu, F., & Jia, R. (2017). Urban dynamic congestion pricing: an overview and emerging research needs. *International Journal of Urban Sciences*, *21*(sup1), 3-18.

Ciers, J., Mandic, A., Toth, L., & Op't Veld, G. (2019). Carbon Footprint of Academic Air Travel: A Case Study in Switzerland. *Sustainability*, *11*(1), 80.

Civil Aviation Organization. Website: https://www.easa.europa.eu/easa-and-you/environment/icao-aircraft-engine-emissions-databank .Accessed in May 2019.

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., ... & Feigin, V. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, *389*(10082), 1907-1918.

Čokorilo, O. (2016) 'Environmental Issues for Aircraft Operations at Airports', in *Transportation Research Procedia*. doi: 10.1016/j.trpro.2016.05.491.

Čokorilo, O. (2016) 'Environmental Issues for Aircraft Operations at Airports', in Transportation Research Procedia. doi: 10.1016/j.trpro.2016.05.491.

Czerny, A. I. (2010) 'Airport congestion management under uncertainty', *Transportation Research Part B: Methodological*. doi: 10.1016/j.trb.2009.05.005.

Czerny, A. I. (2010) 'Airport congestion management under uncertainty', Transportation Research Part B: Methodological. doi: 10.1016/j.trb.2009.05.005.

Czerny, A. I. and Zhang, A. (2014) 'Airport congestion pricing when airlines price discriminate', *Transportation Research Part B: Methodological*. Pergamon, 65, pp. 77–89. doi: 10.1016/J.TRB.2014.04.004.

Czerny, A. I. and Zhang, A. (2014) 'Airport congestion pricing when airlines price discriminate', Transportation Research Part B: Methodological. Pergamon, 65, pp. 77–89. doi: 10.1016/J.TRB.2014.04.004.

Daniel, J. I. (1995). Congestion pricing and capacity of large hub airports: A bottleneck model with stochastic queues. *Econometrica: Journal of the Econometric Society*, 327-370.

Daniel, J. I. (2001). Distributional consequences of airport congestion pricing. *Journal of Urban Economics*, *50*(2), 230-258.

Daniel, J. I., & Harback, K. T. (2009). Pricing the major US hub airports. *Journal of Urban Economics*, *66*(1), 33-56.

Daniel, J. I., & Pahwa, M. (2000). Comparison of three empirical models of airport congestion pricing. Journal of Urban Economics, 47(1), 1-38.

Dockery, D. W., Pope, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., ... & Speizer, F. E. (1993). An association between air pollution and mortality in six US cities. *New England journal of medicine*, *329*(24), 1753-1759.

Dones, R., Heck, T., Bauer, C., Hirschberg, S., Bickel, P., Preiss, P., ... & De Vlieger, I. (2005). ExternE-Pol Externalities of Energy: Extension of accounting framework and policy applications. *Paul Scherer Institute*.

Egea-Lopez, E., Vales-Alonso, J., Martinez-Sala, A. S., Pavon-Marino, P., & García-Haro, J. (2005, July). Simulation tools for wireless sensor networks. In *proceedings of the international symposium on performance evaluation of computer and telecommunication systems (SPECTS05)* (p. 24).

emission trends. *Philosophical Transactions A, 366*(1882), 3863.

Environmental Protection Agency (EPA) (2011) Exposure factors handbook: 2011 edition. Washington, DC; National Center for Environmental assessment. Website:

Environmental Protection Agency (EPA), 2010. Air Trends Air Quality Design Values. Website:

Environmental Protection Agency (EPA), 2010. Health | Particulate Matter | Air & Radiation | Website: https://web.archive.org/web/20061002182639/http://epa.gov/pm/health.html

Environmental Protection Agency (EPA), 2014. 2014 National Emissions Inventory Report. Website: https://gispub.epa.gov/neireport/2014/

Environmental Protection Agency (EPA), 2016. Climate Change | The Social Cost of Carbon. Website: https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html

Environmental Protection Agency (EPA), 2017. BenMAP-CE Regional Datasets. Last updated: July 5, 2017. Website: https://www.epa.gov/benmap/benmap-ce-regionaldatasets.

Environmental Protection Agency (EPA), 2018. Benefits Mapping and Analysis Program (BenMAP)| BenMAP-CE Manual and Appendices. Website: https://www.epa.gov/benmap/benmap-ce-manual-and-appendices

Fann, N., Lamson, A. D., Anenberg, S. C., Wesson, K., Risley, D., & Hubbell, B. J. (2012). Estimating the national public health burden associated with exposure to ambient $PM_{2.5}$ and ozone. *Risk Analysis: An International Journal*, *32*(1), 81-95.

FAA, 2018a.Los Angeles International Airport (LAX) Runway Status Lights (RWSLs). Website: https://www.faa.gov/air_traffic/publications/atpubs/ntap_jan_18/SW17000.html

FAA, 2018b. What is the largest cause of delay in the National Airspace System? Website: https://www.faa.gov/nextgen/programs/weather/faq/#faq1

FAA, 2019. ASPM Taxi Times: Definitions of Variables. Website: https://aspmhelp.faa.gov/index.php/ASPM_Taxi_Times:_Definitions_of_Variables

Federal Aviation Administration (FAA) (2014). Traffic Flow Management System Counts (TFMSC). Website: https://aspm.faa.gov/tfms/sys/Main.asp

Federal Aviation Administration (FAA) (2018). Federal Aviation Administration aerospace forecasts. Website: https://www.faa.gov/data_research/aviation/aerospace_forecasts/

Fleuti, E., and P. Hofmann. 2005. Aircraft APU Emissions at Zurich Airport. Zurich, Switzerland: Unique (Flughafen Zürich AG).

Flores-Fillol, R. (2010). Congested hubs. *Transportation Research Part B: Methodological*, *44*(3), 358-370.

Gallager, R. G. (2012). *Discrete stochastic processes* (Vol. 321). Springer Science & Business Media.

Gallagher, K., & Taylor, R. (2003). *International trade and air pollution: The economic costs of air emissions from waterborne commerce vessels in the United States* (pp. 03-08). Tufts University.

Ghude, S. D., Chate, D. M., Jena, C., Beig, G., Kumar, R., Barth, M. C., ... & Pithani, P. (2016). Premature mortality in India due to $PM_{2.5}$ and ozone exposure. *Geophysical Research Letters*, *43*(9), 4650-4658.

Gillen, D., Jacquillat, A., & Odoni, A. R. (2016). Airport demand management: The operations research and economics perspectives and potential synergies. *Transportation Research Part A: Policy and Practice*, *94*, 495-513.

Greene, D. L., Baker Jr, H. H., & Plotkin, S. E. (2010). Reducing greenhouse gas emissions from US transportation.

Goodkind, A. L., Coggins, J. S., & Marshall, J. D. (2014). A spatial model of air pollution: the impact of the concentration-response function. *Journal of the Association of Environmental and Resource Economists*, 1(4), 451-479.

Haight, F. A. (1967). Handbook of the Poisson distribution.

Hansen, J., Sato, M., Ruedy, R., Kharecha, P., Lacis, A., Miller, R., et al. (2006). Dangerous humanmade

Hsu, H. H., Adamkiewicz, G., Houseman, E. A., Vallarino, J., Melly, S. J., Wayson, R. L., ... & Levy, J. I. (2012). The relationship between aviation activities and ultrafine particulate matter concentrations near a mid-sized airport. *Atmospheric Environment*, *50*, 328-337. https://cfpub.epa.gov/ncea/risk/recordisplay.cfm?deid=20563 https://www.epa.gov/air-trends/air-quality-design-values

Hu, R., Chen, L., & Zheng, L. (2018). Congestion pricing and environmental cost at Guangzhou Baiyun International Airport. Journal of Air Transport Management, 70, 126-132.

Hu, S., Fruin, S., Kozawa, K., Mara, S., Winer, A. M., & Paulson, S. E. (2009). Aircraft emission impacts in a neighborhood adjacent to a general aviation airport in Southern California. *Environmental science & technology*, *43*(21), 8039-8045.

Hudda, N., Gould, T., Hartin, K., Larson, T. V., & Fruin, S. A. (2014). Emissions from an international airport increase particle number concentrations 4-fold at 10 km downwind. *Environmental science & technology*, *48*(12), 6628-6635.

Hung, G. R., Whitehouse, S. R., O'Neill, C., Gray, A. P., & Kissoon, N. (2007). Computer modeling of patient flow in a pediatric emergency department using discrete event simulation. *Pediatric emergency care*, *23*(1), 5-10.

Hutyra, L. R., Duren, R., Gurney, K. R., Grimm, N., Kort, E. A., Larson, E., & Shrestha, G. (2014). Urbanization and the carbon cycle: Current capabilities and research outlook from the natural sciences perspective. *Earth's Future*, *2*(10), 473-495.

Hyslop, N. P. (2009). Impaired visibility: the air pollution people see. *Atmospheric Environment*, *43*(1), 182-195.

IEA. (2009). *Transport, Energy and CO2—Moving Towards Sustainability.* Paris, France: International Energy Agency.

Iñaki Ucar, Bart Smeets and Arturo Azcorra (2018). simmer: Discrete-Event Simulation for R. Journal of Statistical Software

interference with climate: A GISS modelE study. *Atmospheric Chemistry and Physics, 7*, International Civil Aviation Organization (ICAO) (2013). Present and future trends in aircraft noise and emissions (Assembly 38th Session No. Working paper).

International Air Transport Association (2014). IATA 2015 Report on Alternative Fuels.

International Civil Aviation Organization (ICAO) (2016a). ICAO Global Framework for Aviation Alternative Fuels. International.

International Civil Aviation Organization (2016b). Resolution A39-3: Consolidated statement of continuing ICAO policies and practices related to environmental protection—Global Market-based Measure (MBM) scheme (39th general assembly).

International Coalition for Sustainable Aviation (ICSA) (2018). Website: https://www.icsa-aviation.org/issues/cutting-climate-pollution/global-market-based-measure/

Iowa State University (2019). Windrose of Los Angeles International Airport. Website: https://mesonet2.agron.iastate.edu/sites/windrose.phtml?station=LAX&network=CA_ASOS

International Civil Aviation Organization (ICAO) (2019). Aircraft Engine Emissions. Website: https://www.icao.int/environmental-protection/Pages/aircraft-engine-emissions.aspx

Iqbal, S., Clower, J. H., Hernandez, S. A., Damon, S. A., & Yip, F. Y. (2012). A review of disaster-related carbon monoxide poisoning: surveillance, epidemiology, and opportunities for prevention. *American journal of public health*, *102*(10), 1957-1963.

Jaap (2015). Gridlock on the ground: How airlines can respond to airport congestion. *Article by McKinsey & Company*.

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2006). Discrete-event simulation of health care systems. In *Patient flow: Reducing delay in healthcare delivery* (pp. 211-252). Springer, Boston, MA.

Jacquillat, A., & Odoni, A. R. (2018). A roadmap toward airport demand and capacity management. *Transportation Research Part A: Policy and Practice*, *114*, 168-185.

Kapetanaki, S. M., Silkstone, G., Husu, I., Liebl, U., Wilson, M. T., & Vos, M. H. (2009). Interaction of Carbon Monoxide with the Apoptosis-Inducing Cytochrome c− Cardiolipin Complex. *Biochemistry*, *48*(7), 1613-1619.

Kinsey, J. S., Timko, M. T., Herndon, S. C., Wood, E. C., Yu, Z., Miake-Lye, R. C., ... & Anderson, B. E. (2012). Determination of the emissions from an aircraft auxiliary power unit (APU) during the Alternative Aviation Fuel Experiment (AAFEX). *Journal of the Air & Waste Management Association*, *62*(4), 420-430.

Kirschke, S., Bousquet, P., Ciais, P., Saunois, M., Canadell, J. G., Dlugokencky, E. J., ... & Cameron-Smith, P. (2013). Three decades of global methane sources and sinks. *Nature geoscience*, *6*(10), 813.

Koudis, G. S., Hu, S. J., Majumdar, A., Jones, R., & Stettler, M. E. (2017). Airport emissions reductions from reduced thrust takeoff operations. *Transportation Research Part D: Transport and Environment*, *52*, 15-28.

Krewski, D., Jerrett, M., Burnett, R. T., Ma, R., Hughes, E., Shi, Y., ... & Thun, M. J. (2009). *Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality* (No. 140). Boston, MA: Health Effects Institute.

Kurniawan, J. S., & Khardi, S. (2011). Comparison of methodologies estimating emissions of aircraft pollutants, environmental impact assessment around airports. *Environmental impact assessment review*, *31*(3), 240-252.

Laden, F., Schwartz, J., Speizer, F. E., & Dockery, D. W. (2006). Reduction in fine particulate air pollution and mortality: extended follow-up of the Harvard Six Cities study. *American journal of respiratory and critical care medicine*, *173*(6), 667-672.

Le Quéré, C., Moriarty, R., Andrew, R. M., Peters, G. P., Ciais, P., Friedlingstein, P., ... & Boden, T. A. (2015). Global carbon budget 2014. *Earth System Science Data*, *7*(1), 47-85.

Lee, D. S., Pitari, G., Grewe, V., Gierens, K., Penner, J. E., Petzold, A., ... & Iachetti, D. (2010). Transport impacts on atmosphere and climate: Aviation. *Atmospheric Environment*, *44*(37), 4678-4734.

Lepeule, J., Laden, F., Dockery, D., & Schwartz, J. (2012). Chronic exposure to fine particles and mortality: an extended follow-up of the Harvard Six Cities study from 1974 to 2009. *Environmental health perspectives*, *120*(7), 965-970.

Levine, M. E. (1969). Landing fees and the airport congestion problem. *The Journal of Law and Economics*, *12*(1), 79-108.

Lin, M. H., & Zhang, Y. (2017). Hub-airport congestion pricing and capacity investment. *Transportation Research Part B: Methodological*, 101, 89-106.

Lin, M. H., & Zhang, Y. (2017). Hub-airport congestion pricing and capacity investment. Transportation Research Part B: Methodological, 101, 89-106.

Lobo, P., Hagen, D. E., & Whitefield, P. D. (2012). Measurement and analysis of aircraft engine PM emissions downwind of an active runway at the Oakland International Airport. *Atmospheric environment*, *61*, 114-123.

Los Angeles World Airports(LAWA) Official Site | 10-Year Summary of Passengers. Website: https://www.lawa.org/

Los Angeles World Airports(LAWA) Official Site | Lax Air Cargo. (n.d.). Website: https://www.lawa.org/

Los Angeles World Airports(LAWA). 2015 Sustainability Report. Los Angeles World Airports.

Los Angeles World Airports. (2016). Facts about modernizing LAX. *LAWA.* 10/2016. page 2.

Lu, C. (2018). When will biofuels be economically feasible for commercial flights? Considering the difference between environmental benefits and fuel purchase costs. *Journal of cleaner production*, *181*, 365-373.

Lu, C., & Morrell, P. (2006). Determination and applications of environmental costs at different sized airports–aircraft noise and engine emissions. *Transportation*, *33*(1), 45-61.

Masri, S., Garshick, E., Coull, B. A., & Koutrakis, P. (2017). A novel calibration approach using satellite and visibility observations to estimate fine particulate matter exposures in Southwest Asia and Afghanistan. *Journal of the Air & Waste Management Association*, *67*(1), 86-95.

May 2, 2017. Website: https://www.epa.gov/benmap/benmap-ce-regionaldatasets.

Mayer, C., & Sinai, T. (2003). Network effects, congestion externalities, and air traffic delays: Or why not all delays are evil. American Economic Review, 93(4), 1194-1215.

Mazaheri, M., Johnson, G. R., & Morawska, L. (2008). Particle and gaseous emissions from commercial aircraft at each stage of the landing and takeoff cycle. *Environmental science & technology*, *43*(2), 441-446.

McCollum, D., & Yang, C. (2009). Achieving deep reductions in U.S. transport greenhouse gas emissions: Scenario analysis and policy implications. *Energy Policy*, *37* (12), 5580-5596.

McCollum, D., Gould, G., & Greene, D. (2009). *Greenhouse Gas Emissions from Aviation and Marine Transportation: Mitigation Potential and Policies.* Arlington, Virginia: Pew Center on Global Climate Change.

Meinshausen, M., Meinshausen, N., Hare, W., Raper, S.C.B., Frieler, K., Knutti, R., et al. (2009). Greenhouse-gas emission targets for limiting global warming to 2°C. *Nature, 458*(7242), 1158–1162.

Monsalud, A., Ho, D. and Rakas, J. (2015) ‘Greenhouse gas emissions mitigation strategies within the airport sustainability evaluation process’, *Sustainable Cities and Society*. doi: 10.1016/j.scs.2014.08.003.

Monsalud, A., Ho, D. and Rakas, J. (2015) ‘Greenhouse gas emissions mitigation strategies within the airport sustainability evaluation process’, Sustainable Cities and Society. doi: 10.1016/j.scs.2014.08.003.

Moolgavkar, S. H. (2000). Air pollution and hospital admissions for chronic obstructive pulmonary disease in three metropolitan areas in the United States. *Inhalation Toxicology*, *12*, 75-90.

Moolgavkar, S. H. (2003). Provide r*evised analyses of time-series studies of air pollution and health. Special report*, 183-198.

Morrison, S. A. (1986). A survey of road pricing. *Transportation Research Part A: General*, *20*(2), 87-97.

Nahlik, M. J., Chester, M. V., Ryerson, M. S., & Fraser, A. M. (2016). Spatial differences and costs of emissions at US airport hubs. *Environmental science & technology*, *50*(8), 4149-4158.

NAS, M. C., Newell, R., Allen, M., Auffhammer, M., Forest, C. E., NAS, I. F., ... & Rose, S. (2017). Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide. *National Academies Press. Washington, DC Available at< https://www. nap. edu/catalog/24651/valuing-climate-damagesupdating-estimation-of-the-social-cost-of> Accessed May*, *30*(2017), 273-312.

National Ambient Air Quality (2004). 40 CFR Part 50 - National Primary and Secondary Ambient Air Quality Standards. § 50.7 National primary and secondary ambient air quality standards for $PM_{2.5}$. amended at 69 FR 45595, July 30, 2004.

Owen, B.; Lee, D. S.; Lim, L. Flying into the Future: Aviation Emissions Scenarios to 2050. Environ. Sci. Technol. 2010, 44, 2255− 2260.

Pels, E., & Verhoef, E. T. (2004). The economics of airport congestion pricing. *Journal of Urban Economics*, *55*(2), 257-277.

Pope III, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., & Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Jama*, *287*(9), 1132-1141.

Pope III, C. A., Burnett, R. T., Thurston, G. D., Thun, M. J., Calle, E. E., Krewski, D., & Godleski, J. J. (2004). Cardiovascular mortality and long-term exposure to particulate air pollution: epidemiological evidence of general pathophysiological pathways of disease. *Circulation*, *109*(1), 71-77.

Pope III, C. A., & Dockery, D. W. (2006). Health effects of fine particulate air pollution: lines that connect. *Journal of the air & waste management association*, *56*(6), 709-742.

Pope III, C. A., Ezzati, M., & Dockery, D. W. (2009). Fine-particulate air pollution and life expectancy in the United States. *New England Journal of Medicine*, *360*(4), 376-386.

Pope III, C. A., Burnett, R. T., Turner, M. C., Cohen, A., Krewski, D., Jerrett, M., ... & Thun, M. J. (2011). Lung cancer and cardiovascular disease mortality associated with ambient air pollution and cigarette smoke: shape of the exposure–response relationships. *Environmental health perspectives*, *119*(11), 1616-1621.

Postorino, M. N. and Mantecchini, L. (2014) 'A transport carbon footprint methodology to assess airport carbon emissions', *Journal of Air Transport Management*. doi: 10.1016/j.jairtraman.2014.03.001.

Postorino, M. N. and Mantecchini, L. (2014) 'A transport carbon footprint methodology to assess airport carbon emissions', Journal of Air Transport Management. doi: 10.1016/j.jairtraman.2014.03.001.

Psanis, C., Triantafyllou, E., Giamarelou, M., Manousakas, M., Eleftheriadis, K., & Biskos, G. (2017). Particulate matter pollution from aviation-related activity at a small airport of the Aegean Sea Insular Region. *Science of the Total Environment*, *596*, 187-193.

Raaschou-Nielsen, O., Andersen, Z. J., Beelen, R., Samoli, E., Stafoggia, M., Weinmayr, G., ... & Xun, W. W. (2013). Air pollution and lung cancer incidence in 17 European cohorts:

prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *The lancet oncology*, *14*(9), 813-822.

Rahila, R., & Siddiqui, M. (2014). Review on effects of particulates; sulfur dioxide and nitrogen dioxide on human health. *International Research Journal of Environmental Sciences*, *3*(4), 70-73.

Ratliff, G.; Sequeira, C.; Waitz, I.; Ohsfeldt, M.; Thrasher, T.; Graham, G.; Thompson, T.; Graham, M.; Thompson, T. Aircraft Impacts on Local and Regional Air Quality in the United States, Report No. PARTNER-COE-2009-002; PARTNER, 2009.

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10), 895.

Roberts, S. (2004). Biologically plausible particulate air pollution mortality concentration-response functions. Environmental health perspectives, 112(3), 309-313.

Rogelj, J., Hare, B., Nabel, J., Macey, K., Schaeffer, M., Markmann, K., et al. (2009). Halfway to Copenhagen, no way to 2◦C. *Nature Reports Climate Change, 3*(0907), 81–83.

Rumchev, K., Brown, H., & Spickett, J. (2007). Volatile organic compounds: do they present a risk to our health?. *Reviews on environmental health*, *22*(1), 39-56.

Rupp, N. G. (2009). Do carriers internalize congestion costs? Empirical evidence on the internalization question. *Journal of Urban Economics*, *65*(1), 24-37.

Sacks, J. D., Lloyd, J. M., Zhu, Y., Anderton, J., Jang, C. J., Hubbell, B., & Fann, N. (2018). The Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP–CE): A tool to estimate the health and economic benefits of reducing air pollution. *Environmental Modelling & Software*, *104*, 118-129.

San Jose, R., Pérez, J. L., Pérez, L., & González, R. M. (2018, August). A Health Impact Assessment of Traffic Restrictions during Madrid NO2 Episode. In *IOP Conference Series: Earth and Environmental Science* (Vol. 182, No. 1, p. 012003). IOP Publishing.

Sasaki, M., Suzuki, A. and Drezner, Z. (1999) 'On the selection of hub airports for an airline hub-and-spoke system', *Computers & Operations Research*. Pergamon, 26(14), pp. 1411–1422. doi: 10.1016/S0305-0548(99)00043-X.

Sasaki, M., Suzuki, A. and Drezner, Z. (1999) 'On the selection of hub airports for an airline hub-and-spoke system', Computers & Operations Research. Pergamon, 26(14), pp. 1411–1422. doi: 10.1016/S0305-0548(99)00043-X.

Schäfer, K., Jahn, C., Sturm, P., Lechner, B., & Bacher, M. (2003). Aircraft emission measurements by remote sensing methodologies at airports. *Atmospheric Environment*, *37*(37), 5261-5271.

Schipper, Y. (2004). Environmental costs in European aviation. *Transport policy*, *11*(2), 141-154.

Schlenker, W. and Walker, W. R. (2016) 'Airports, air pollution, and contemporaneous health', *Review of Economic Studies*. doi: 10.1093/restud/rdv043.

Schlenker, W. and Walker, W. R. (2016) 'Airports, air pollution, and contemporaneous health', Review of Economic Studies. doi: 10.1093/restud/rdv043.

Schlesinger, R. B. (2007). The health impact of common inorganic components of fine particulate matter ($PM_{2.5}$) in ambient air: a critical review. *Inhalation toxicology*, *19*(10), 811-832.

Schulman, L. L., & Scire, J. S. (1980). *Buoyant line and point source (BLP) dispersion model user's guide. Final report* (No. PB-81-164642). Environmental Research and Technology, Inc., Concord, MA (USA).

Schürmann, G., Schäfer, K., Jahn, C., Hoffmann, H., Bauerfeind, M., Fleuti, E., & Rappenglück, B. (2007). The impact of NOx, CO and VOC emissions on the air quality of Zurich airport. *Atmospheric Environment*, *41*(1), 103-118.

Sheppard, L. (2003). Ambient air pollution and nonelderly asthma hospital admissions in Seattle, Washington, 1987-1994. *Revised analyses of time-series studies of air pollution and health. Special report*.

Shirmohammadi, F., Sowlat, M. H., Hasheminassab, S., Saffari, A., Ban-Weiss, G., & Sioutas, C. (2017). Emission rates of particle number, mass and black carbon by the Los Angeles International Airport (LAX) and its impact on air quality in Los Angeles. *Atmospheric Environment*, *151*, 82-93.

Silva, H. E., Verhoef, E. T. and van den Berg, V. A. C. (2014) 'Airlines' strategic interactions and airport pricing in a dynamic bottleneck model of congestion', *Journal of Urban Economics*. Academic Press, 80, pp. 13–27. doi: 10.1016/J.JUE.2013.08.002.

Silva, H. E., Verhoef, E. T. and van den Berg, V. A. C. (2014) 'Airlines' strategic interactions and airport pricing in a dynamic bottleneck model of congestion', Journal of Urban Economics. Academic Press, 80, pp. 13–27. doi: 10.1016/J.JUE.2013.08.002.

Simaiakis, I., & Balakrishnan, H. (2010). Impact of congestion on taxi times, fuel burn, and emissions at major airports. *Transportation Research Record*, *2184*(1), 22-30.

Simaiakis, I., Khadilkar, H., Balakrishnan, H., Reynolds, T. G., & Hansman, R. J. (2014). Demonstration of reduced airport congestion through pushback rate control. *Transportation Research Part A: Policy and Practice*, *66*, 251-267.

Stettler, M. E. J., Eastham, S., & Barrett, S. R. H. (2011). Air quality and public health impacts of UK airports. Part I: Emissions. *Atmospheric Environment*, *45*(31), 5415-5424.

TFMSC - Aspmhelp. (n.d.). Website: https://aspmhelp.faa.gov/index.php/TFMSC

U.S. Department of Transportation, 2014. Guidance on Treatment of the Economic Value of a Statistical Life. (PDF). 13 June 2014.

U.S. Environmental Protection Agency, 2013 U.S. Transportation Sector Greenhouse Gas Emissions. Office of Transportation and Air Quality EPA-420-F13-033a (2013).

U.S. Environmental Protection Agency, 2016. The Social Cost of Carbon: Estimating the Benefits of Reducing Greenhouse Gas Emissions. Website:

U.S. Environmental Protection Agency, 2017c. BenMAP-CE Regional Datasets. Last updated:

U.S. Environmental Protection Agency, 2018a. User's Guide for The AERMOD Meteorological Preprocessor (n.d.).
Website: https://www3.epa.gov/ttn/scram/7thconf/aermod/aermet_userguide.pdf

U.S. Environmental Protection Agency, 2018b. Air Quality Design Values. Website:

Ucar, I., Smeets, B., & Azcorra, A. (2017). simmer: Discrete-Event Simulation for R. *arXiv preprint arXiv:1705.09746*.

Unal, A., Hu, Y., Chang, M. E., Odman, M. T., & Russell, A. G. (2005). Airport related emissions and impacts on air quality: Application to the Atlanta International Airport. *Atmospheric Environment*, *39*(32), 5787-5798.

US Environmental Protection Agency (USEPA). (2017a). Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE).

Vaidyanathan, B. S., Miller, D. M., & Park, Y. H. (1998, December). Application of discrete event simulation in production scheduling. In *1998 Winter Simulation Conference. Proceedings (Cat. No. 98CH36274)* (Vol. 2, pp. 965-971). IEEE.

Verhoef, E. T. (2010) 'Congestion pricing, slot sales and slot trading in aviation', *Transportation Research Part B: Methodological*. doi: 10.1016/j.trb.2009.07.002.

Verhoef, E. T. (2010) 'Congestion pricing, slot sales and slot trading in aviation', Transportation Research Part B: Methodological. doi: 10.1016/j.trb.2009.07.002.

Voorhees, A. S., Fann, N., Fulcher, C., Dolwick, P., Hubbell, B., Bierwagen, B., & Morefield, P. (2011). Climate change-related temperature impacts on warm season heat mortality: a proof-of-concept methodology using BenMAP. *Environmental science & technology*, *45*(4), 1450-1457.

Voorhees, A. S., Wang, J., Wang, C., Zhao, B., Wang, S., & Kan, H. (2014). Public health benefits of reducing air pollution in Shanghai: a proof-of-concept methodology with application to BenMAP. *Science of the Total Environment*, *485*, 396-405.

Walters, A. A. (1961). The theory and measurement of private and social cost of highway congestion. *Econometrica: Journal of the Econometric Society*, 676-699.

Wan, Y., Jiang, C. and Zhang, A. (2015) 'Airport congestion pricing and terminal investment: Effects of terminal congestion, passenger types, and concessions', *Transportation Research Part B: Methodological*. Pergamon, 82, pp. 91–113. doi: 10.1016/J.TRB.2015.10.006.

Wan, Y., Jiang, C. and Zhang, A. (2015) 'Airport congestion pricing and terminal investment: Effects of terminal congestion, passenger types, and concessions', Transportation Research Part B: Methodological. Pergamon, 82, pp. 91–113. doi: 10.1016/J.TRB.2015.10.006.

Wardrop, J. G. (1952). Road paper. some theoretical aspects of road traffic research. *Proceedings of the institution of civil engineers*, *1*(3), 325-362.

Wayson, R. L., Fleming, G. G., & Iovinelli, R. (2009). Methodology to estimate particulate matter emissions from certified commercial aircraft engines. *Journal of the Air & Waste Management Association*, *59*(1), 91-100.

Weitzman, M. L. (1974). Prices vs. quantities. *The review of economic studies*, *41*(4), 477-491.

Westerdahl, D., Fruin, S. A., Fine, P. L., & Sioutas, C. (2008). The Los Angeles International Airport as a source of ultrafine particles and other pollutants to nearby communities. *Atmospheric Environment*, *42*(13), 3143-3155.

Wilkerson, J. T., Jacobson, M. Z., Malwitz, A., Balasubramanian, S., Wayson, R., Fleming, G., ... & Lele, S. K. (2010). Analysis of emission data from global commercial aviation: 2004 and 2006. *Atmospheric Chemistry and Physics*, *10*(13), 6391-6408.

Windisch, J., Väätäinen, K., Anttila, P., Nivala, M., Laitila, J., Asikainen, A., & Sikanen, L. (2015). Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. *Applied energy*, *149*, 315-325.

Wolfe, P., Davidson, K., Fulcher, C., Fann, N., Zawacki, M., & Baker, K. R. (2019). Monetized health benefits attributable to mobile source emission reductions across the United States in 2025. *Science of The Total Environment*, *650*, 2490-2498.

Wolff, R. W. (1982). Poisson arrivals see time averages. *Operations Research*, *30*(2), 223-231.

Wood, E. C., Herndon, S. C., Timko, M. T., Yelvington, P. E., & Miake-Lye, R. C. (2008). Speciation and chemical evolution of nitrogen oxides in aircraft exhaust near airports. *Environmental science & technology*, *42*(6), 1884-1891.

World Health Organization. (2016). Health risk assessment of air pollution: General principles. *Copenhagen: WHO*. 2287–2312.

World Health Organization. (2019). Air pollution | Ambient air pollution: Pollutants. Website: https://www.who.int/airpollution/ambient/pollutants/en/

World Health Organization. WHO Air Quality Guidelines for Europe, WHO Regional Office for Europe, 2000, Copenhagen, Denmark. *WHO Regional Publications, European Series*, (91).

Yılmaz (2017). Emissions from passenger aircrafts at Kayseri Airport, Turkey. *Journal of Air Transport Management*, 58, 176-182.

Yim, S. H. L., Stettler, M. E. J. and Barrett, S. R. H. (2013) 'Air quality and public health impacts of UK airports. Part II: Impacts and policy assessment', *Atmospheric Environment*. doi: 10.1016/j.atmosenv.2012.10.017.

Yim, S. H. L., Stettler, M. E. J. and Barrett, S. R. H. (2013) 'Air quality and public health impacts of UK airports. Part II: Impacts and policy assessment', Atmospheric Environment. doi: 10.1016/j.atmosenv.2012.10.017.

Yim, S. H., Lee, G. L., Lee, I. H., Allroggen, F., Ashok, A., Caiazzo, F., ... & Barrett, S. R. (2015). Global, regional and local health impacts of civil aviation emissions. *Environmental Research Letters*, *10*(3), 034001.

Yim, S. H., Stettler, M. E., & Barrett, S. R. (2013). Air quality and public health impacts of UK airports. Part II: Impacts and policy assessment. *Atmospheric environment*, *67*, 184-192.

Yun, Y., Gao, R., Yue, H., Li, G., Zhu, N., & Sang, N. (2015). Synergistic effects of particulate matter (PM10) and SO2 on human non-small cell lung cancer A549 via ROS-mediated NF-κB activation. *Journal of Environmental Sciences*, *31*, 146-153.

Zanobetti, A., Franklin, M., Koutrakis, P., & Schwartz, J. (2009). Fine particulate air pollution and its components in association with cause-specific emergency admissions. Environmental Health, 8(1), 58.

Zhang, A. and Zhang, Y. (2010) 'Airport capacity and congestion pricing with both aeronautical and commercial operations', *Transportation Research Part B: Methodological*, 44(3), pp. 404–413. doi: 10.1016/j.trb.2009.09.001.

Zhang, A. and Zhang, Y. (2010) 'Airport capacity and congestion pricing with both aeronautical and commercial operations', Transportation Research Part B: Methodological, 44(3), pp. 404–413. doi: 10.1016/j.trb.2009.09.001.

Zhang, A., & Czerny, A. I. (2012). Airports and airlines economics and policy: An interpretive review of recent research. *Economics of Transportation*, *1*(1-2), 15-34.

Zhang, A., & Zhang, Y. (2006). Airport capacity and congestion when carriers have market power. *Journal of urban Economics*, *60*(2), 229-247.

Zhu, Y., Fanning, E., Yu, R. C., Zhang, Q., & Froines, J. R. (2011). Aircraft emissions and local air quality impacts from takeoff activities at a large International Airport. *Atmospheric Environment*, *45*(36), 6526-6533.

Zhu, Y., Hinds, W. C., Kim, S., & Sioutas, C. (2002b). Concentration and size distribution of ultrafine particles near a major highway. *Journal of the air & waste management association*, *52*(9), 1032-1042.

Zhu, Y., Hinds, W. C., Kim, S., Shen, S., & Sioutas, C. (2002a). Study of ultrafine particles near a major highway with heavy-duty diesel traffic. *Atmospheric environment*, *36*(27), 4323-4335.